NBER WORKING PAPER SERIES

MARKET ENTRY COSTS, PRODUCER HETEROGENEITY, AND EXPORT DYNAMICS

Sanghamitra Das
Mark J. Roberts
James R. Tybout

Working Paper 8629
http://www.nber.org/papers/w8629

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
December 2001

We would like to thank Daniel Donath for excellent research assistance, and Behzad Diba, Martin Evans, Keith Head, Michael Keane, Andrew Levin, Ariel Pakes, Nina Pavcnik, John Rust, and Nadia Soboleva for helpful discussions. This research was supported by the World Bank and the National Science Foundation (Grant No.SES-0095574). The views expressed herein are those of the authors and not necessarily those of the National Bureau of Economic Research.

Market Entry Costs, Producer Heterogeneity, and Export Dynamics
Sanghamitra Das, Mark J. Roberts and James R. Tybout
NBER Working Paper No. 8629
December 2001
JEL No. F10, L10

ABSTRACT

As the exchange rate, foreign demand, production costs and export promotion policies evolve, manufacturing firms are continually faced with two issues: Whether to be an exporter, and if so, how much to export. We develop a dynamic structural model of export supply that characterizes these two decisions and estimate the model using plant-level panel data on Colombian chemical producers. The model embodies uncertainty, plant-level heterogeneity in export profits, and sunk entry costs for plants breaking into foreign markets. Our estimates, and the simulation exercises that they support, yield several implications. First, entry costs are typically large, but vary greatly across producers. Second, there is substantial cross-plant heterogeneity in gross expected export profit streams. Third, these large entry costs make expectations about future exporting conditions important for many producers, so changes in the exchange rate regime that are credible induce much more entry than those that are not. Fourth, however, most of the entry and exit takes place among marginal exporters who contribute little to aggregate export revenues. Finally, subsidies on export earnings have a much larger impact on export revenues (per dollar spent) than subsidies that reduce the entry costs faced by new exporters.

Sanghamitra Das
Planning Unit
Indian Statistical Institute
7 S J S Sansanwal Marg
New Delhi 110016, India
dasm@isid.isid.ac.in

Mark J. Roberts
Department of Economics
The Pennsylvania State University
University Park, PA 16802
and NBER
mroberts@psu.edu

James R. Tybout
Department of Economics
The Pennsylvania State University
University Park, PA 16802
and NBER
jxt32@psu.edu

1. Overview

In developing countries, manufacturing sectors that respond to export stimuli are highly prized. By making greater imports feasible, these sectors help to generate the traditional gains from trade. They also stabilize domestic employment by venting surplus production in foreign markets, and they may even generate efficiency gains through trade-related technology diffusion (e.g., Westphal, 2001). But export supply responses are poorly understood. Seemingly similar stimuli have given rise to very different export responses in different countries and time periods, making it difficult to know whether the next devaluation or export subsidy scheme will generate a surge or a trickle of new exports.

Several micro explanations might account for the puzzle of export responsiveness. First, a strong export response may require the entry of non-exporters into foreign markets. But to break into foreign markets, firms must establish marketing channels, learn bureaucratic procedures, and develop new packaging or product varieties. In the presence of these entry costs, expectations about future market conditions can critically affect current behavior, and doubts about the permanence of export promotion packages may discourage foreign market entry.[1]

Second, entry costs make firms' export supply responses dependent upon their previous exporting status. Firms that already export can adjust their volumes at marginal production costs, while those that do not must bear the sunk costs of breaking in before any exports are possible. These two margins of adjustment—volume and entry—have distinct determinants and lead to different supply elasticities, so seemingly similar industries with different degrees of foreign market presence may respond quite differently to exporting stimuli.

[1] Start-up costs are the focus of the analytical literature on export hysteresis (Baldwin and Krugman, 1989; Dixit, 1989; Krugman, 1989).

Finally, even within narrowly-defined industries, firms are heterogeneous in terms of their production costs and their product characteristics. Depending upon the distribution of these characteristics across firms, there may be many firms poised on the brink of foreign market entry, or just a few. Thus, when these cross-plant distributions of marginal cost and foreign demand are unobservable, widely different export responses are possible under seemingly similar conditions.

In this paper we develop a dynamic optimizing model of export supply that captures each of these micro phenomena, and we econometrically fit the model to plant-level panel data on Colombian producers of industrial chemicals. We use our estimates to simulate export responses to a shift in the mean of the exchange rate process. In doing so we quantify the roles of sunk costs, exporting experience and firm heterogeneity in shaping export responsiveness. We also demonstrate a methodology that should be relevant for other applications involving firms' decisions to diversify into new geographic or product markets.

Our estimates imply that entry costs are large and variable across plants. Further, we find a great deal of cross-plant heterogeneity in gross exporting profits. Most producers anticipate only very modest profits from exporting, while a handful enjoys far more favorable foreign demand and/or marginal cost conditions.

These features of the Colombian chemical industry shape the results of our policy simulations. First, the fact that sunk entry costs are large makes expectations about future exporting conditions important for many plants. Thus we find that a moderate shift in the mean of the log exchange rate process induces sustained net entry by new exporters and rising export volumes *if* producers view it as a credible regime shift. On the other hand, the exact same change in the exchange rate process induces far less entry when producers retain their old beliefs about the exchange rate process.

Second, profits for the major exporters are sufficiently large to keep them in the export market under any reasonable policy scenario. So the foreign market entry and exit that takes place is concentrated among small suppliers who have a relatively minor effect on export volumes. It follows that, while expectations have a dramatic effect on the number of exporters, their effect on the *volume* of exports is much more modest.

Third, policies that promote exports through per-unit subsidies generate far larger responses per peso spent than policies that promote exports through lump-sum transfers for new exporters. The reasons are that (1) exporters that need a subsidy to get into export markets are almost always marginal suppliers; (2) these same exporters face relatively high entry costs, and (3) large incumbent exporters, who account for most of the industry's foreign sales are unaffected by entry subsidies, but positively affected by volume subsidies.

Finally, because of the cross-plant heterogeneity in our data, our simulations imply diminishing returns to sunk or fixed cost subsidies in terms of export revenues generated per peso spent. This is because, as subsidy rates rise, entrants at the margin are increasingly less suited to exporting and sell increasingly little abroad.

In addition to quantifying the micro phenomena behind export responses, our model of exporting behavior makes several methodological contributions. First, because we use a dynamic structural framework, we are able to estimate sunk costs in dollars rather than simply test for their existence.[2] These costs are critical to policy evaluation but they have rarely been estimated

[2] Earlier studies of export market participation have focused on the null hypothesis that sunk costs don't matter, but have not been structural and thus have not *quantified* sunk costs (Roberts and Tybout, 1997a; Campa, 1998; Bernard and Jensen, 2001; Bernard and Wagner, 2001).

because they can only be identified by their very non-linear effects on market participation patterns. Second, although we model producers as choosing foreign prices and export quantities, we cast the estimating equations in terms of the variables that we actually observe—export revenues and variable costs. We thus sidestep the usual problem that arises with plant-level survey data of constructing proxies for prices and quantities from poorly measured variables.

The remainder of the paper has four sections. Section 2 develops an dynamic empirical model of both the plant's discrete decision to participate in the export market and it's continuous decision on the level of export revenue. Section 3 discusses econometric issues. Section 4 presents empirical results and section 5 discusses their implications for export supply response. Finally, section 6 offers concluding remarks.

2. An Empirical Model of Exporting Decisions with Sunk Costs and Heterogeneity

Our model of export supply is based on several key assumptions. First, products are differentiated across firms, and the foreign and domestic market for each is monopolistically competitive. This eliminates strategic competition, but it ensures that each firm faces a downward-sloping marginal revenue function in each market. Second, producers are heterogeneous in terms of their marginal production costs and the foreign demand schedules they face for their products, so export profit trajectories vary across firms. Third, future realizations on the exchange rates, marginal costs, and foreign demand shifters are unknown, but each evolves according to a known Markov process. Fourth, firms must pay stochastic sunk start-up costs to initiate exports. Finally, marginal costs do not respond to output shocks. This assumption implies that shocks that shift the domestic demand schedule do not affect the optimal level of exports, so it allows us to focus on the export market only.[3]

2.1 *Gross export profits and revenues*

We begin by characterizing the export profit stream that firms earn once they have broken into foreign markets. The magnitude of this stream depends upon things that shift the marginal cost schedule, like technology shocks and factor prices, and things that shift the foreign demand schedule, like foreign aggregate demand and the real exchange rate. We assume that marginal costs and foreign demand are Cobb-Douglas functions of these factors, so that gross export profits are log-linear in the same set of arguments:

$$\ln(\pi_{it}) = \psi_0 z_i + \psi_1 e_t + \psi_2 t + \nu_{it} \tag{1}$$

Here π_{it} is firm i's gross operating profits in the export market during year t ($i = 1, \ldots n$; $t = 1, \ldots, T$), z_i is a vector of time-invariant, firm-specific characteristics that lead to differences in marginal costs and product desirability, e_t is the log of the real exchange rate and t is a time trend that captures secular trends in factor prices, technical efficiency and foreign demand that are general to all firms.[4] Finally, v_{it} is a stationary, serially-correlated disturbance term that captures all idiosyncratic shocks to foreign demand and marginal production costs.

Controlling for the trend, export profits evolve over time with exogenous shocks to e_t and v_{it}. We assume that the exchange rate follows a first-order Markov process with normally distributed shocks and we collect the parameters that characterize this process in the parameter

[3] The assumption appears to be reasonable for the industry, country, and time period we will study, since some excess capacity was present. Estimates of average variable cost functions revealed little dependence on within-plant temporal output fluctuations.

[4] Some characteristics, such as domestic market size or capital stock, do change over time but including these as time-varying state variables requires an increase in the complexity of the model that makes it intractable.

vector Ω_e. Because the profit function disturbance, v_{it}, picks up unobserved shocks on both the demand and the cost side, it requires a less restrictive specification. To allow for multiple sources of shocks while keeping firms' dynamic optimization problems tractable, we assume that v_{it} can be represented as the sum of *m* normally-distributed, first-order Markov processes, which we collect in the vector $x_{it} = (x_{it}^1, x_{it}^2, \ldots, x_{it}^m)'$.[5] This assumption implies that v_{it} is normal and has a stationary *ARMA*(*m*, *m-1*) representation. We collect the parameters that characterize the distribution of x_{it} and v_{it} in the vector Ω_x.

Our data set includes information on export revenues but not on export profits, so we cannot estimate $\Psi = (\psi_0, \psi_1, \psi_2)$ and Ω_x directly from equation (1).[6] To surmount this problem we assume that firms incur no adjustment costs when changing from one positive level of exports to another. Then short-run profit maximization implies the standard mark-up relationship between price (P_{it}) and marginal cost (C_{it}): $P_{it}(1 - \eta_i^{-1}) = C_{it}$, where $\eta_i > 1$ is a firm-specific export-demand elasticity. Also, given our earlier assumption that marginal costs do not depend upon output levels, we can multiply both sides of this relationship by output and re-write it a simple expression linking exporting profits and exporting revenues (R_{it}): $\pi_{it} = R_{it} - Q_{it}C_{it} = \eta_i^{-1}R_{it}$. Substituting $\ln(\eta_i^{-1}R_{it})$ on the left-hand of (1) renders the dependent variable observable up to the vector of firm-specific foreign demand elasticities, $\eta = \{\eta_i\}$, $i=1,2,...n.$, which become parameters to be estimated.

[5]It would be straightforward to allow for higher-order exchange rate processes in the same way that we treat v_{it}. However to keep the number of state variables reasonably small we do not do so.

[6] Most plant- and firm-level data sets, including ours, lack information on the prices, export quantities, and factor prices that would be necessary to identify marginal revenue and marginal cost schedules.

2.2 *The export market participation rule*[7]

Because we have used a logarithmic functional form for equation (1), gross export profits are always positive. Nonetheless, firms may choose not to export for several reasons. First, firms that aren't already exporting face the sunk start-up costs of establishing distribution channels, learning bureaucratic procedures, and adapting their products and packaging for foreign markets. Second, exporters incur some fixed costs each period to maintain a presence in foreign markets, including minimum freight and insurance charges, and the costs of monitoring foreign customs procedures and product standards. We now characterize firms' exporting decisions in the face of these costs.

Denote the fixed costs of exporting $\Gamma_F - \varepsilon_{1it}$, where Γ_F is a component common to all firms and ε_{1it} captures all variation in fixed costs across firms and time. Also, if the i^{th} firm did not export in period *t-1*, assume it must pay the additional start-up costs, $\Gamma_S z_i + \varepsilon_{1it} - \varepsilon_{2it}$, where Γ_S is a vector of coefficients on the fixed plant characteristics, z_i, and $\varepsilon_{it} = (\varepsilon_{1it}, \varepsilon_{2it})$ is a vector of firm specific shocks that is normally distributed with zero mean and covariance matrix Ω_{ε}. Following Rust (1988), we assume that each component of ε_{it} is serially uncorrelated and independent of x_{it} and e_t.[8]

Finally, define the binary variable y_{it} to take a value of one during periods when the firm exports and zero otherwise. Then, denoting the gross profit function in equation (1) by $\pi(x_{it}, z_i, e_t, t)$, and assuming that all sunk costs are borne in the first year of exporting, net current export

[7] Dixit (1989), Baldwin and Krugman (1989) and Krugman (1989) develop theoretical models that characterize export market participation decisions in the presence of sunk entry costs. Our representation of the decision to export is a variant of their basic framework.

[8] These are Rust's (1988) conditional independence assumptions. They substantially simplify the numerical solution of the firm's dynamic optimization problem. Note that the errors ε_{it} can also be interpreted as the managers' transitory optimization errors when choosing export quantities or prices, as well as variation in fixed and sunk costs.

profits accruing to the i^{th} firm in year t may be written as:

$$u(e_t, x_{it}, z_i, t, y_{it}, y_{it-1}, \varepsilon_{it}) = \begin{cases} \pi(x_{it}, z_i, e_t, t) - \Gamma_F + \varepsilon_{1it} & \textit{if } y_{it} = 1 \textit{ and } y_{it-1} = 1 \\ \pi(x_{it}, z_i, e_t, t) - \Gamma_F - \Gamma_S z_i + \varepsilon_{2it} & \textit{if } y_{it} = 1 \textit{ and } y_{it-1} = 0 \\ 0 & \textit{if } y_{it} = 0 \end{cases} \quad (2)$$

Note that net profits depend on the firm's export participation in the previous year, y_{it-1}, because that determines whether it must pay the sunk entry costs to export in year t.[9] Thus the return to becoming an exporter today includes the expected value of being able to continue exporting next period without incurring start-up costs, which in turn depends upon the perceived distribution of future gross exporting profits (e.g., Dixit, 1989).

We shall assume that each period, prior to making their exporting decisions, firms observe the current period realizations on the arguments of their gross profit function (1): z_i, e_t, and x_{it}. These variables all follow first-order Markov processes, so they provide all the information available at time t on the possible future paths for gross exporting profits. Suppressing i subscripts, at time 0 a firm that maximizes its discounted expected profit stream over a planning horizon of H years will therefore choose the sequence of decision rules $Y = \{y_t = y(e_t, x_t, z, ,t, y_{t-1}, \varepsilon_t, \theta)\}_{t=0}^{H}$ that solves:

$$\max_{Y} \quad E_0\{\sum_{t=0}^{H} \delta^t u(e_t, x_t, z, t, y_{t-1}, y_t, \varepsilon_t, \theta)\} \quad (3)$$

Here E_0 is the expectation operator conditioned on information available at time 0, δ is a discount

[9] Equation (2) implies that firms completely lose their investment in start-up costs if they are absent from the export market for a single year. Earlier studies suggest that these investments depreciate very quickly, and that firms which most recently exported two years ago must pay nearly as much to re-enter foreign markets as firms that never exported (Roberts and Tybout, 1997a). In light of these findings, and given that more general representations make structural estimation intractable, we consider (2) to be a reasonable abstraction.

factor $0 < \delta < 1$, and θ is the parameter vector $\theta = (\Psi, \Gamma_F, \Gamma_S, \Omega_x, \Omega_e, \Omega_\varepsilon)$.

To characterize the decision rule $y(\cdot)$, note that expression (3) is equal to the value function that solves the Bellman equation:

$$V_t(e_t, x_t, z, t, y_{t-1}, \varepsilon_t, \theta) = \max_{y_t \in \{0,1\}} [u(e_t, x_t, z, t, y_{t-1}, y_t, \varepsilon_t, \theta) + \delta EV_t(e_t, x_t, z, t, y_t, \theta)], \qquad (4)$$

where EV_t is the expected value of V_{t+1} over the future paths of the state variables e, x, and ε:

$$EV_t(e_t, x_t, z, t, y_t, \theta) = \qquad (5)$$
$$\int_{e_{t+1}} \int_{x_{t+1}} \int_{\varepsilon_{t+1}} V_{t+1}(e_{t+1}, x_{t+1}, z, t, y_t, \varepsilon_{t+1}, \theta) dF_{ex}(e_{t+1}, x_{t+1}, | e_t, x_t, \Omega_x, \Omega_e) dF_\varepsilon(\varepsilon_{t+1} | \Omega_\varepsilon),$$

and dF_{ex} and dF_ε are the conditional distribution functions for the period t+1 values of the vectors (e, x) and ε, respectively.[10] Thus the sequence of optimal decision rules satisfies:

$$y(e_t, x_t, z, t, y_{t-1}, \varepsilon_t, \theta) = \operatorname*{argmax}_{y_t \in \{0,1\}} [u(e_t, x_t, z, t, y_{t-1}, y_t, \varepsilon_t, \theta) + \delta EV_t(e_t, x_t, z, t, y_t, \theta)] \qquad (6)$$

Given the parameter vector θ and our distributional assumptions for the exogenous state variables $(e_t, x_{it}, \varepsilon_{it})$, equations (6) and (1) determine optimal foreign market participation patterns and export profits for the i^{th} firm. Also the relationship $\pi_{it} = \eta_i^{-1} R_{it}$ converts profits to revenues. Hence, aggregating over firms, these three equations provide a framework for

[10] This model satisfies the regularity conditions required for the existence and uniqueness of the value function: time separability of the profit function, a Markovian transition density for the state variables, and a discount rate less than one. See Rust (1995), section 2.

assessing the roles of heterogeneity, sunk costs, expectations, and history in shaping export responsiveness at the industry level. In the next section we discuss the econometric issues that arise in estimating equations (1) and (6) with micro panel data.

3. Econometric Issues

We will base our estimates on annual panel data describing all manufacturing plants in the Colombian chemical industry operating continuously over an 11 year period.[11] For each plant and year we observe a few fixed plant characteristics (z_i), total sales revenues (TR_{it}), total variable costs (TVC_{it}), and export revenues (R_{it}). Given R_{it}, we can, of course, infer each plant's discrete decisions concerning whether to export (y_{it}). Finally, we have time-series observations on the real peso-dollar exchange rate (e_t), adjusted for the relevant export subsidies (Ocampo and Villar, 1995). We do not observe plants' gross export profits, output prices, input prices, physical quantities sold, or any direct information on the sunk and fixed costs of exporting.

Our objective is to obtain estimates of the parameter vector $\theta = (\Psi, \Gamma_F, \Gamma_S, \Omega_x, \Omega_e, \Omega_\varepsilon)$ using the likelihood function for observed trajectories of the endogenous variables, (y_{it}, R_{it}). By equations (1) and (6), y_i and R_i depend upon $(e, x_i, z_i, \varepsilon_i)$, where variables without t subscripts denote entire trajectories over the sample period (t = 1, ... T). However, both the x_i and the ε_i trajectories are unobserved, so to state the likelihood function in terms of our data we must take the expectation of the joint density function for $(y_i, R_i, e, x_i, z_i, \varepsilon_i)$ over (x_i, ε_i). Expectations with respect to ε_i are straightforward to calculate because these disturbances are serially uncorrelated and independent of (x_i, z_i, R_i, e). But the x_i trajectories are serially correlated and

[11]Firm-level data would have been preferable but these were unavailable.

related to (e, z_i, R_i) by equation (1). Matters are further complicated by the fact that we do not see the export revenues that were available to plants in the years when they are were not exporting. That is, R_{it} is censored at zero when $y_{it} = 0$.

To deal with these problems, we base the likelihood function on observed profits of exporters, $\pi_i^a = \eta_i^{-1} R_i^a$ where R_i^a is the sub-vector of R_i for which R_{it} is strictly positive. Then, after taking expectations over ε_i, the likelihood function for the ith plant becomes:

$$L_i = \int_{x_i} P(y_i | e, x_i, z_i, \theta) g(x_i | \eta_i^{-1} R_i^a, e, z_i, \Psi, \Omega_x) h(\eta_i^{-1} R_i^a | e, z_i, \Psi, \Omega_x) dx_i \tag{7}$$

The product of the three components of the integrand is the joint distribution for y_i, R_i^a and x_i, conditioned on z_i and *e*. (The integration over x_i is *mT*-dimensional where *m* is the number of state variables in *x*.) The first component of this product, $P(\cdot|\cdot)$, is the conditional probability for the exporting trajectory, y_i, based on the decision rule (6), after taking the expectation over ε_i. The second component, $g(\cdot|\cdot)$, gives the distribution for the exogenous state variables, x_i, conditional on the observed export revenue stream (among other factors). Note that because x_i is serially correlated, export revenues in *each* year convey information on x_{it} for *all t*. The last component, $h(\cdot|\cdot)$, which corresponds to equation (1), is the density for profits from foreign sales during the exporting years, given the exogenous conditioning variables. All three components of the integrand in equation (7) depend on the profit function parameters (Ψ, Ω_x) and the vector of firm demand elasticities, η, but only $P(\cdot|\cdot)$ depends upon Γ_F, Γ_S, or Ω_ε.

Given the need for several layers of numerical integration (discussed below), it is not feasible to obtain estimates of all of the parameters that appear in (7) from a one-step maximum likelihood estimator .[12] To handle the complexity we proceed in stages. First, we estimate those parameters that can be identified outside the model—the vector of firm-specific foreign demand elasticities, η , and the parameters that govern the exchange rate process, Ω_e. Next we estimate the profit function parameters (Ψ, Ω_x) using the conditional density $h(\eta_i^{-1}R_i^a | z_i, e, \Psi, \Omega_x)$. Then using these parameters, we construct the plant-specific conditional density for the *mT* profit shocks, $g(x_i | \eta_i^{-1}R_i^a, e, z_i, \Psi, \Omega_x)$. Finally, taking ($\Psi$, Ω_x), η and Ω_e as given, we construct the likelihood function for observed export market participation patterns and maximize this function over (Γ_F, Γ_S, Ω_ε). This approach limits the number of parameters we solve for in the computationally-intensive third stage, which requires repeated multi-dimensional integration (see equations 5 and 7). The costs of this approach are that, first, it is less efficient than single-stage maximum likelihood, and second, it means that the standard errors for (Γ_F, Γ_S, Ω_ε) based on the information matrix from the final stage likelihood function are asymptotically biased downward. We deal with the latter problem by constructing bootstrap standard errors.

3.1 *Estimating demand elasticities and the exchange rate process*

To estimate the vector of plant specific demand elasticities, we assume that each plant's demand elasticity is the same at home and abroad, making η_i^{-1} one minus the ratio of *total* (domestic and foreign) variable production costs (TVC*)* to *total* revenue (TR) by the mark-up rule. Then, assuming that true variable costs are measured up to a zero-mean error by labor and intermediate input costs, we estimate $(\eta_i)^{-1}$ as a plant-specific average of the right-hand-side of this

[12] For a discussion of the computational burden of dynamic discrete choice models, see Rust (1995).

expression across observations: $(\hat{\eta}_i)^{-1} = \frac{1}{T}\sum_{t=1}^{T}\left(1 - \frac{TVC_{it}}{TR_{it}}\right)$. Discrepancies between estimated and true elasticities will induce measurement error in profits and will be reflected in v_{it}. Given our identifying restriction that e_t is independent of x_i and ε_i trajectories, there is no advantage to estimating the exchange rate process jointly with other parameters. Hence, at this preliminary stage we also obtain the parameters of the exchange rate process by fitting a simple AR(1) process to macro data on e_t.

3.2 *Estimating profit function parameters*

Next we obtain maximum likelihood estimates of the profit function. By earlier assumption, the disturbance term of this function can be written as $v_{it} = \ell' x_{it}$ where $\ell = \begin{pmatrix}1, & 1, & \cdots & 1\end{pmatrix}'$ is an m by one vector of ones and the elements of x_i follow normal AR(1) processes. We we write the latter as:

$$x_{it} = Mx_{it-1} + \omega_{it}, \tag{8}$$

where $\omega_i \sim N(0,Q)$, $M = \begin{bmatrix} \lambda_1 & 0 & \cdots & 0 \\ 0 & \lambda_2 & & \vdots \\ \vdots & & \ddots & 0 \\ 0 & \cdots & 0 & \lambda_m \end{bmatrix}$ and $Q = \begin{bmatrix} q_1 & 0 & \cdots & 0 \\ 0 & q_2 & & \vdots \\ \vdots & & \ddots & 0 \\ 0 & \cdots & 0 & q_m \end{bmatrix}$.[13] This rendering of the AR(1) processes implies the parameter vector describing the evolution of the state variables x_{it} is $\Omega_x = (M, Q)$. More substantively, assuming that each plant begins with a random draw from the steady state distribution of x_{it}, it implies that the profit shocks v_{it} are distributed

---

[13] The assumption that the elements of ω_{it} are orthogonal to one another is innocuous. If they were not, we could re-state the model in terms of orthogonal shocks by using a Cholesky decomposition of their covariance matrix.

$N\left(0, \ell' Q[I - M^2]^{-1}\ell\right)$. Also, for all $k \neq 0$, $E[\nu_{it}\nu_{it-k}] = \ell' M^{|k|} Q\left[(I - M^2)^{-1}\right] \ell$ and $E[v_{it}v_{jt-k}] = 0 \; \forall \, i \neq j$ (e..g., Chow, 1983). These relationships define the conditional density $h(\eta_i^{-1} R_i^a | \, e, z_i, \Psi, \Omega_x)$, which in turn provides a basis for estimation of the parameters Ψ and Ω_x.

Two final complications must be dealt with. First, we apply our estimator to the unbalanced panel of observations for which exports are positive. But firms self-select into the export market partly on the basis of v_{it}, so we need to correct for selectivity bias. In principle we could handle this problem by maximizing a likelihood function based on (7) over the entire parameter vector θ. However, as noted earlier, this approach is computationally very burdensome. We therefore use a variant of Heckman's (1979) selection correction that amounts to including a Mills ratio in (1). This variable is based on a simple reduced form probit equation that explains each plant's probability of exporting as a function of its strictly exogenous characteristics: location, business type, and initial capital stock.[14]

Second, firms that have just entered the export market and firms that are about to leave the export market do not typically report a full year's worth of export revenues.[15] We assume that their reported values represent some fraction of the year drawn from a uniform distribution on the (0,1] interval, and these fractions are independent across plants and time. Then we numerically integrate them out of the likelihood function based on $h(\eta_i^{-1} R_i^a | \, e, z_i, \Psi, \Omega_x)$.

Once we have obtained estimates of Ψ, Ω_x, and η we can construct the conditional

---

[14]Monte Carlo experiments confirm that this procedure does a good job of recovering true values for Ψ and Ω_x.

[15]Brooks (2000) finds that, for a given plant, the first and final year of exporting data are significantly smaller.

distribution $g(x_i \,|\, \eta_i^{-1} R_i^a, e, z_i, \Psi, \Omega_x)$ that appears in (7). First, we use equation (1) and the data to calculate the profit shocks $v_{it} = \ell' x_{it} = \eta_i^{-1} R_{it} - \left[\psi_0 z_i + \psi_1 e_t + \psi_2 t\right]$ for all exporting years. Then, collecting all of these observable realizations on ν_{it} for the i^{th} plant in the column vector ν_i^a, and exploiting well-known properties of the multivariate normal distribution, we obtain:

$$g(x_i \,|\, \eta_i^{-1} R_i^a, e, z_i, \Psi, \Omega_x) = g(x_i \,|\, \nu_i^a) = N\left(\Sigma_{x\nu} \Sigma_{\nu\nu}^{-1} \nu_i^a,\ \Sigma_{xx} - \Sigma_{x\nu} \Sigma_{\nu\nu}^{-1} \Sigma_{x\nu}'\right). \qquad (9)$$

Here x_i is the column vector obtained by stacking the year-specific x_{it}'s, and representative blocks of the matrices that appear in (9) are defined by:

$$\begin{aligned} \sum\nolimits_{xx} &= \left\{ E(x_{it} x_{it+s}') \right\} = \left\{ M^{|s|} Q (I - M^2)^{-1} \right\}, \\ \sum\nolimits_{x\nu} &= \left\{ E(x_{it} v_{it+s}) \right\} = \left\{ M^{|s|} Q (I - M^2)^{-1} \ell \right\} \quad \text{and} \\ \sum\nolimits_{\nu\nu} &= \left\{ E(v_{it} v_{it+s}) \right\} = \left\{ \ell' M^{|s|} Q (I - M^2)^{-1} \ell \right\}. \end{aligned}$$

Several features of the density (9) merit comment. First, although our notation does not show it explicitly, the dimensions and composition of $\Sigma_{x\nu}$ and $\Sigma_{\nu\nu}$ vary across plants with their export market participation patterns. Second, equation (9) uses information on a plant's observed exporting revenue to extrapolate to non-exporting years, given the autoregressive processes summarized by Ω_x. Finally, if the i^{th} plant never exports, we do not observe v_{it} in any year so the distribution of x_i is unconditional: $E(x_i) = 0$ and $E(x_i x_i') = \Sigma_{xx}$. This is the only case in which Σ_{xx} is full rank; otherwise the constraint $\ell' x_{it} = \eta_i^{-1} R_{it} - \left[\psi_0 z_i + \psi_1 e_t + \psi_2 t\right]$ makes one component of x_{it} a deterministic function of the others in the exporting years.

3.3 *Estimating sunk and fixed cost parameters*

Having obtained Ψ, Ω_x, η, Ω_e and $g(x_i \,|\, \eta_i^{-1} R_i^a, z_i, e, \Psi, \Omega_x)$, we estimate the remaining parameters in θ by maximizing the sample likelihood function based on (7) over (Γ_F, Γ_S, Ω_ε). Given our assumptions on the exogenous state variables ε_i, x_i, and e_i, exporting decisions in year *t* depend only upon exporting status in year *t-1* and current year information. So, taking expectations over ε_i, the probability of the participation trajectory y_i may be written as a product of year-to-year transition probabilities, conditioned on the other variables:

$$P(y_i \mid e, x_i, z_i, \theta) = \prod_{t=1}^{T} [P(y_{it}=0|e_t, x_{it}, z_i, y_{it-1}=0, \theta)^{(1-y_{it})(1-y_{it-1})} P(y_{it}=0|e_t, x_{it}, z_i, y_{it-1}=1, \theta)^{(1-y_{it})(y_{it-1})} \quad (10)$$
$$P(y_{it}=1|e_t, x_{it}, z_i, y_{it-1}=1, \theta)^{y_{it}y_{it-1}} P(y_{it}=1|e_t, x_{it}, z_i, y_{it-1}=0, \theta)^{y_{it}(1-y_{it-1})}]$$

(Equation A1.2 of appendix 1 provides the expression we use to calculate these transition probabilities.) The likelihood function we use for our final stage of estimation is thus:

$$L(\Gamma_F, \Gamma_S, \Omega_\varepsilon) = \prod_{i=1}^{n} \left\{ \int_{x_i} P[y_i \mid e, x_i, z_i, \theta] g(x_i \mid \eta_i^{-1} R_i^a, e, z_i, \Psi, \Omega_x) \cdot dx_i \right\} \quad (11)$$

When evaluating (11), we integrate over x_i trajectories numerically. Specifically, plant by plant, we sample x_i realizations antithetically from $g(x_i \mid \eta_i^{-1} R_i^a, z_i, e, \Psi, \Omega_x)$, calculate the associated probabilities, $P[y_i \mid e, x_i, z_i, \theta]$, and average them.[16]

Obtaining the transition probabilities themselves is more involved. To calculate them we first evaluate $EV_t(e_t, x_{it}, z_i, t, y_{it}, \theta)$ at $y_{it} = 1$ and $y_{it} = 0$ using backward induction. Then we substitute these values into right-hand side of the decision rule (6) along with the net profit function (2), and we

[16] Antithetic sampling is a way to limit simulation error. It means that for each draw from the relevant density we include its mirror image, ensuring that the set of draws used is symmetric about the true mean. See Rubinstein (1986) for discussion.

take the expectation of the implied y_{it} choice over ε_{it}. We repeat these calculations plant by plant for each sample year, every time the likelihood function is evaluated. Further details are provided in appendix 1.

Each step of the backward induction involves taking expected values over (e_{t+1}, x_{it+1}) realizations, given (e_t, x_{it}). Earlier studies have performed this type of calculation by discretizing the vector of state variables and calculating transition probabilities among each vector of values (Rust, 1988, Das, 1992). The problem with this approach is that it involves a large number of calculations. For example, with 3 continuous state variables and *r* different values per state variable, there are r^3 points in the state space and r^6 transition probabilities involved in the calculations at each stage of the backward induction. With a reasonably long planning horizon, approximation errors compound, and it becomes necessary to use very large values of *r*. This "curse of dimensionality" led Rust (1997) to develop an alternative approach. Instead of treating all possible combinations of values for the discretized state variables as elements of the state space, Rust generates the state space with random draws from the joint probability distribution for the vector of state variables. This solves the dimensionality problem because increasing the number of state variables increases the dimension of each point, but does not increase the number of points over which one integrates.

We adopt Rust's (1997) approach in the present study. First, taking our estimates of Ω_x and Ω_e as given, we draw *G* points from the steady state distribution of (e_t, x_{it}) using antithetic sampling. Then using Ω_x and Ω_e once more, we calculate the G^2 transition probabilities for movements between all possible pairs of these points, thereby constructing a discrete analog to $dF\left(e_{t+1}, x_{it+1} | e_t, x_{it}, \Omega_e, \Omega_x\right)$. Together, these points and transition probabilities allow us to perform the integration at each step of the backward induction algorithm for calculating EV_t.

4. An Application to the Colombian Chemicals Industry

4.1 *Overview of the export patterns*

Although our framework should describe any industry in which exporting is potentially profitable for some firms, it is easiest to identify parameters in those industries which have many exporters, and which exhibit substantial variation in the set of exporters over time. For these reasons, we choose to estimate our model using data on the Colombian chemicals industry for the period 1982 through 1991, which is summarized in table 1 below. Our data set covers 62 major chemical producers that operated continuously during the sample period.[17] It was originally collected by Colombia's Departamento Administrativo Nacional de Estadistica (DANE), and was cleaned as described in Roberts and Tybout (1996).

Note that the Colombian peso depreciated substantially in real terms during the sample period, and that chemical exports simultaneously grew. The expansion was partly due to an increase in the number of exporters, and partly due to increases in the magnitude of foreign sales at the typical exporting plant.[18] Colombian chemicals plants produced 35.00 billion pesos ($236 million US) worth of exports in 1991, of which 29.94 billion came from plants that were exporting in 1984. So entry by new exporters contributed 5.06 out of the 27.10 expansion. Also, of the 62 plants that existed during the entire sample period, 18 exported in all ten years, 26 never exported, and 18 switched exporting status at least once. So, although there were a number of switches, the data exhibit substantial

[17] A more general framework would treat each plant as making simultaneous decisions to enter or exit production and to enter or exit the export market. This would require us to model the sunk costs involved in setting up a plant. In Colombia, most exports over the sample period came from the plants that were continuously in operation and focusing solely on this group of plants is a reasonable starting point that substantially simplifies the empirical model.

[18] The number of chemical plants remains fixed at 62 during the sample because we have excluded producers who enter or exit to simplify the econometrics, so there is some potential for selectivity bias.

persistence. This could be due to serial correlation in the plant-specific state variables, (x_{it}^1, x_{it}^2), or it could be due to sunk entry costs, or some combination of both. Our estimates will shed light on the relative importance of these different forces.

4.2 *First Stage Estimation: Demand Elasticity and the Exchange Rate Process*

Using $(\hat{\eta}_i)^{-1} = \frac{1}{T}\sum_{t=1}^{T}\left(1 - \frac{TVC_{it}}{TR_{it}}\right)$, we begin by obtaining plant-specific estimates of the elasticity of demand. The smallest elasticity is 1.5 and the largest elasticity is constrained to be 20. (Six plants were affected by this constraint.) More than 80 percent of the plants fall between 1.5 and 8.5, and the median elasticity is 5.0. Thus export profits at the typical plant amount to approximately one-fifth of export revenue.[19]

Using data for 1967-1992, we estimate a simple AR(1) process for the real effective export exchange rate calculated by Ocampo and Villar (1995).[20] The coefficients (standard errors in parentheses) are $\hat{e}_t$ = .549 (.429) + 0.883 (.094) e_{t-1} and $\hat{\sigma}^2$ = 0.0043. The Dickey-Fuller test statistic for stationarity is -1.93 and the critical value is -2.78 at a 90 percent confidence level. So, although our point estimates suggest the exchange rate process is stationary, the usual problem with test power prevents us from rejecting the null hypothesis of a unit root.

---

[19] Goldberg and Knetter (1999) use data aggregated to the seven-digit industry level to estimate much lower export demand elasticities for manufactured products. The discrepancy between their results and ours probably traces largely to the fact that individual plants *within* a narrowly defined product category export close substitutes for each others' products.

[20] An AR(2) process fits the data significantly better, but the improvement is minor (R^2 = .85 versus R^2 = .79), and the cost of adding an additional state variable to the model is substantial. Given that the focus of the paper is not on modeling the exchange rate process, we have chosen to keep this aspect of the model as simple as possible.

4.3 *Second Stage Estimation: Profit Function Parameters*

Next we use $\pi_{it} = \hat{\eta}_i^{-1} R_{it}$ to impute export profits and we estimate the profit function (1). Exploratory tests using GMM estimators reject the null hypothesis that the error in the profit function error, ν_{it} , follows a first-order process, but they do not reject the null that it follows an *ARMA*(2,1) (see appendix 2). Thus we model the profit error as the sum of two *AR*(1) processes and use maximum likelihood to estimate the parameters of the profit function Ψ and $\Omega_x = \{Q, M\}$ that describe the evolution of the profit shocks.

The resulting parameter estimates are reported in Table 2. Recall that z_i is meant to capture time-invariant heterogeneity in operating profits. We model these using a set of three size dummies based on domestic sales in the pre-sample year. These dummies should proxy for both product quality and marginal production costs at the beginning of the sample period. Our estimates imply that this type of variation in not particularly important. (Experimentation with other dummies based on geographic location and business type yielded similar results.)

On the other hand, the elasticity of export profits with respect to the exchange is 2.45 and significant. Since the same elasticity describes responses of export *revenues*, it implies that devaluations do more than simply revalue a fixed physical quantity of exports—volumes respond too. The trend term, which picks up secular growth or shrinkage in foreign markets and/or in marginal production costs, adds little. We caution, however, that both of these coefficients are identified with only eleven years of data, so they may not be representative of longer time periods. Replacing the exchange rate and the trend term with annual time dummies did not improve the fit significantly (results not reported), so these variables appear to do a reasonable job of controlling for time effects that are common to all plants. Put differently, barring spatial correlation, our assumption that the disturbances in equation 1 are not correlated across plants seems reasonable. Finally, note that the Mills ratio has the expected sign and is quite significant. This implies that exporting firms enjoy relatively favorable realizations on v_{it} .

The parameters of the x_{it} process, Ω_x, are reported at the bottom of table 2. Each is identified with plant-specific variation and thus is estimated with a good deal of precision. Both λ_1 and λ_2 are less than one in absolute value and significantly different from zero. The variances, q_1 and q_2, are also significantly greater than zero. Thus, as suggested by the specification tests reported in appendix 2, it would be inappropriate to treat the profit function disturbance, v_{it}, as a first-order process. Our interpretation is that profit shocks arise from both demand and cost shocks, each with its own root.

4.4 *Third Stage Estimates: Sunk Costs and Fixed Costs*

Table 3 reports our estimates of $(\Gamma_F, \Gamma_S, \Omega_\varepsilon)$. Four Γ_s estimates appear in this table, corresponding to the four plant size quartiles we distinguish. We report two types of standard errors. The first, reported in column 2, is based on the information matrix for the third stage likelihood function (11), and therefore is not adjusted for the fact that the first and second stage parameters are estimated. The second, reported in column (3), is a bootstrap estimate that recognizes the estimation of all the parameters in the model. [21] Although the bootstrap standard errors suggest that our third stage parameter estimates are not significantly different from zero, this implication is misleading. Their magnitude reflects the fact that, out of the 200 bootstrap samples, several contained very few

[21] To generate the bootstrap standard errors, we repeatedly draw random samples of 248 plants (with replacement) from our data set of 62 plants. Each draw is an entire plant-specific trajectory for the variables that enter our estimator. For each bootstrap sample we repeat all stages of estimation except the exchange rate process. Then we construct the mean squared deviation of bootstrap estimates from the estimates based on our original sample of 62 plants. We used bootstrap samples 4 times the size of the original sample because when only 62 plants are drawn we occasionally get a sample with too few transitions in exporting status to identify all of the parameters. To correct for this difference in sample size, we double the root mean squared deviations (i.e., weight them by $\sqrt{4}$) before reporting them.

exporting plants and thus poorly identified $(\Gamma_F, \Gamma_S, \Omega_\varepsilon)$. Nonetheless, as figure 1 demonstrates, *all* of the bootstrap samples yielded Γ_S parameter estimates greater than zero. Further, the bootstrap samples that yielded large Γ_S estimates also yielded large estimates of $\sigma_{\varepsilon 1}$ and $\sigma_{\varepsilon 2}$. Thus we estimate the ratios of sunk costs to the noise in the profit function for entrants with much greater precision. The vector $(\frac{\Gamma_{S1}}{\sigma_{2\varepsilon}}, \frac{\Gamma_{S2}}{\sigma_{2\varepsilon}}, \frac{\Gamma_{S3}}{\sigma_{2\varepsilon}}, \frac{\Gamma_{S4}}{\sigma_{2\varepsilon}})$ is estimated to be (4.06, 2.27, 2.60, 1.81) and the associated vector of asymptotic *z*-ratios is (1.39, 2.76, 2.53, 2.55). So for all size categories except the smallest, sunk entry costs are clearly greater than zero.

Turning to the parameter estimates themselves, note first that sunk costs appear to fall with plant sizes, suggesting that big plants with large domestic market shares are in a better position to step into international markets. (Γ_{s1} is the average export market entry cost among plants in the smallest size quartile, Γ_{s2} is the average entry cost for plants in the second quartile, and so on.) This pattern could reflect existing contacts and distribution channels among large firms, the types of products large firms produced, or to the mix of people they employ.

One advantage of structural estimation is that it allows us to calculate the sunk costs of entering foreign markets in currency units. Table 3 implies that, at a discount factor of 0.9, the *expected* sunk costs of breaking into export markets vary from 108 to 242 million 1986 pesos, depending upon which plant size category we are describing. In 1999 US dollars, these figures are $730,000 and $1.6 million, respectively.

The fixed cost Γ_F estimate is very close to zero, and as already discussed, our bootstrap distribution suggests that these costs are negligible on average. Recall, however, that fixed costs are $\Gamma_F - \varepsilon^1_{it}$, and our bootstrap distribution bounds σ_{ε_1} above zero. So fixed costs are important at least some of the time for some of the plants. Finally, note that σ_{ε_2} is similar in magnitude and also bounded above zero by the bootstrap distribution, implying that sunk costs vary considerably across plant, even after controlling for their size class.

Given that the estimation procedure involves several stages and repeated multi-dimensional integration, we explored the sensitivity or our estimates to the fineness of the grid used for integration over one-step-ahead realizations on exogenous state variables and the number of trajectories drawn per plant for integration over x_i . Coefficient estimates varied roughly 20 percent with grid draws and x_i draws. However, this range of variation did not decline as we increased the number of grid points and x_i trajectories per plant to the maximum values feasible with our hardware. (The maximum number of grid points, G, we used was 300 and the maximum number of x_i trajectories per plant we used was 50.)

5. Implications for Export Supply

5.1 *Profits, option values and transition probabilities*

To explore the implications of sunk costs and plant profit heterogeneity, we calculate the plant-specific gross expected value of exporting in year t before netting out sunk costs:

$$\begin{aligned}\tilde{V}_{it} = \int \Big[& \pi(x_{it}, z_i, e_t, t) - \Gamma_F + \\ & \delta\Big(EV_t(x_{it}, z_i, e_t, t, y_{it} = 1) - EV_t(x_{it}, z_i, e_t, t, y_{it} = 0)\Big)\Big] \cdot g(x_{it} | R_i^a, e_t, z_i) dx_{it} .\end{aligned}$$

This expression has a current profit component (first line) and an option value component (second line), which measures the value of being able to export next period without paying entry costs. Note that $\tilde{V}_{it}$ is an expectation over the unobservable x_{it} values, so it shows less cross-plant heterogeneity than was actually present.

The gross expected value of exporting for the first year in our sample (t=1982) is compared with expected sunk entry costs, $\Gamma_S z_i$, plant by plant, in figure 2. Plants are sorted by sunk cost category, then by ascending $\tilde{V}_{i,1982}$. The circled lines in the figure are the sunk costs that are estimated for each of the four plant types, where the type is defined by the plant's size in the domestic market. For the left-most group of plants, the ones with the smallest domestic output levels, the sunk cost of entry (242 million pesos) exceeds the gross expected export value for all the plants. This is also true for the second group of plants, which faced a sunk entry cost of 136 million pesos, but in this case both the gross expected export value and sunk cost are lower than for the first group. Ignoring noise in sunk costs and $x_{i,1982}$ realizations, no non-exporter in either group would find it profitable to enter the export market. For the remaining two groups of plants the profit heterogeneity is more extreme and some plants have gross expected export values that are high enough that they would enter the export market. For the largest plants, expected profit heterogeneity is substantial. Note that a single plant stands out with exceptional export profits.

For several reasons, figure 2 should not be used to predict which plants will actually be in the export market: it averages out noise in sunk costs and $x_{i,1982}$ realizations, and it provides no information on plants' prior export experience. To illustrate the difference that prior experience makes, we construct the 1982 plant-specific transition probabilities, once again taking expectations over $x_{i,1982}$. Figure 3 shows the probability that each plant will remain an exporter, assuming it exported in the previous year, and the probability that each plant will enter the export market, assuming it did not export in the previous year. Plants are sorted in order of ascending $\tilde{V}_{i,1982}$. The probability of remaining an exporter, once in, is above .8 for virtually all plants. That is, $P(\tilde{V}_{i,1982} + \varepsilon_{1i,1982} > 0)$ is quite high for most plants. In contrast, the probability of *entering* the market

$P(\tilde{V}_{i,1982} - \Gamma_S z_i + \varepsilon_{1i,1982} > 0)$ is much lower for virtually all plants, and below .1 for half of the plants. Only a few plants have entry probabilities that exceed .5, indicating that the sunk entry costs are a significant entry hurdle for most producers.

We now isolate the role of option values in determining export market participation patterns. This component of $\tilde{V}_{i,1982}$ depends on the plants' expectations of future market conditions and is bounded by their sunk costs. To illustrate how important the option value is as a source of the plant's total export value, figure 4 plots current profit net of fixed costs, Γ_F, and total export value for each of the non-exporting plants in 1982. The difference between the two curves is the option value. If there were no sunk costs of entry, the option value would be zero and the two curves in figure 4 would be identical. The figure demonstrates that the option value is a large component of the total value of the plant. In fact, in many cases the current profits that would be earned by being an exporter are close to zero, so that the option value is the largest component of $\tilde{V}_{i,1982}$. Even among firms with substantial current profits from exporting, the option value still accounts for about two-thirds of total export value. As expectations of future market conditions improve, the option value term increases and can induce entry even if current profits are unaffected.

Total industry exports depend on both the number of plants exporting and the foreign sales volume of each plant. Figure 5 illustrates the distribution of export revenue for all plants in 1982, sorted by export revenue. The upper line, denoted by triangles, gives the cumulative export revenue earned by the 25 plants that were actually in the export market in that year. Total export revenues were approximately 6.3 billion pesos. Differences in the size of the exporters are obvious, with the largest two plants accounting for almost half of the industry revenue. Figure 5 also illustrates the predicted revenues that would have been earned by each of the non-exporting plants if they had been induced to enter the market. The cumulative predicted exports of the 37 non-exporting plants are approximately 2.6 billion pesos. These plants would have increased industry export revenue by approximately 41 percent if they had been in the market, but no one of the non-exporters would have added more than several percentage points by itself.

5.2 *Simulated Effect of a Devaluation*

The export supply response to a devaluation reflects adjustments on two margins: entry-exit and output adjustments among incumbents. To quantify each type of response we simulate firms' reactions to a permanent change in the exchange rate process that depreciates the steady state value of the peso by 10 percent, leaving its variance unchanged.[22] The regime shift takes place in period 1 and we track firms reactions over the following nine periods. Firms always begin period 1 in their observed state, thereafter all realizations on x and e are simulated. We calculate expected reactions by simulating 300 exchange rate trajectories under each scenario and averaging each firm's responses.

The effect on the number of exporting plants is illustrated in the top panel of figure 6. The first simulation, which we label "credible devaluation," characterizes reactions when the regime switch is correctly anticipated and believed by all plants. By this terminology we mean that all plants use the correct new regime parameters for the exchange rate process when they formulate expectations about future profits. Under this assumption we calculate an expected first-year increase of 4.5 percent in the number of exporting plants. The expected number of exporters continues to expand by a total of 12.2 percent over the nine-year horizon we simulate.

---

[22] This is accomplished by increasing the intercept of the estimated autoregressive process for the log of the exchange rate. Given the parameter estimates reported in section 4.2, the steady state mean of the logarithmic exchange rate is .549/(1-.883) = 4.69. Using the relationships between the mean and variance of a normal and a log normal random variable, a two percent increase in the mean of the log exchange rate translates into a 10 percent increase in the mean of the exchange rate itself.

Figure 6 also shows expected responses to a "non-credible" regime switch in which producers incorrectly continue to use the pre-reform exchange rate parameters in their evaluation of future profit trajectories. Under this scenario there is virtually no response in the expected number of exporting plants. Even after 5 years of experience with the more favorable exchange rate, no new entry has occurred. This markedly different outcome is solely due to differences in expectations, since gross operating profits evolve in the same way under both scenarios. Thus a substantial, permanent change in the exchange rate process may not induce entry if firms view the outcomes as transitory shocks generated by the old regime.

The effect of the same devaluation on the level of export revenue is illustrated in the bottom panel of table 6. Here expected export revenues increase approximately 5 percent in the first year of the new policy and approximately 37.5 percent over the nine-year horizon. The increase in total export revenue is driven primarily by the expansion of the existing exporters and this is insensitive to the perceived credibility of the exchange rate change. The difference in revenue growth between the credible and non-credible devaluation is the result of the entry of the new exporters in the credible regime. While there is significant new entry, the new exporters are relatively small and so they make only a small contribution to total export revenue.

5.3 *Alternative Policies to Subsidize Exports*

The case for export promotion policies is controversial.[23] Nonetheless, it is quite common to find significant promotional regimes in place. In this section we shall ignore the question of whether

[23]Those who advocate export promotion (e.g., Westphal, 2001) argue that exports generate various positive spillovers, while those who are opposed to export promotion (e.g., Panagaria, 1999) discount the importance of these spillover effects.

export promotion is desirable and address the positive quantitative issue of how effective various types of promotion are in terms of their impact on export volumes.

Aside from currency devaluation, governments in developing countries and elsewhere have used a variety of tools to encourage manufactured exports. (Panagaria,1999, provides a critical review.) In terms of value, the most significant ones are usually direct subsidies linked to plant's export revenues.[24] Preferential credit and insurance are commonly provided by official export promotion agencies and/or administered through the financial sector. Export processing zones provide duty-free access to imported inputs that are subject to tariffs among non-exporters. Policies that affect transport costs through the public development of port facilities do the same. All of these subsidies increase the profits of plants once they are in the export market and thus tend to induce volume adjustments among incumbent exporters, as well as net entry.

A second policy option is to directly subsidize the sunk costs that plants incur to enter export markets.[25] Matching grant programs that subsidize information acquisition or investments in technology acquisition for export development fall under this heading, presuming that these are one-shot start-up costs.[26] Support for participation in trade fairs might also be classified as this type of

[24] In Colombia, the most important subsidy has been a tax rebate that is proportional to foreign sales. This rebate has been delivered in the form of negotiable certificates (Certificado Abono Tributarios) that recipients can use to retire their taxes or sell on a secondary market. Other export subsidies have included a duty drawback scheme (Plan Vallejo), insurance against exchange rate risk on dollar-denominated export loans (discontinued in 1977), and subsidized export credit (from PROEXPO). As Ocampo and Villar (1995) document, the combined value of these subsides fluctuated between 16 and 27 percent of export sales for manufacturing overall during the sample period. We use Ocampo and Villar's real effective export exchange rate to estimate our model, so although we do not isolate their effects, these subsidies are built into our analysis.

[25] Alternatively, creation of export trade groups that collect information on sources of demand and match foreign buyers and domestic producers can also act to reduce one substantial cost of entry for new exporters. Information deficiencies were identified as significant impediments to exporting by Colombian manufacturers in a recent survey. See Roberts and Tybout (1997) for discussion.

[26] Pursell (1999) notes that such programs have gained popularity rapidly at the World Bank during the past decade. "The justification for these projects is generally that there are exporting firms that would increase

policy, given that it reduces the costs of establishing a foreign clientele. Sunk cost subsidies encourage entry, but if they do not affect marginal production costs they should not affect export volume decisions, *given* foreign market participation. Further, they also encourage exit if they are available repeatedly to the same producer because they reduce the incentive to avoid re-entry costs by remaining in foreign markets during unprofitable periods.

A third type of export promotion provides subsidies that are not directly tied to plants' export level but rather are flat payments designed to cover the annual fixed costs of operating in the export market. The same types of policies that help to reduce entry costs can fall under this heading, provided that regular expenditures are required to maintain foreign clients and/or adapt the product to evolving tastes, technologies and characteristics of competing products. Unless they shift the marginal production cost schedule, fixed costs subsidies resemble sunk cost subsidies in that they operate on the entry-exit margin but not the volume margin. However, given that they do not affect the threshold costs associated with exit and re-entry, their effect should be primarily on the number of exporters rather than the long run rate of turnover among exporting plants.

Using our estimated model, we simulate each of these policy options. First we explore the effects of a per-unit subsidy equal to 10% of their export revenue. Second, we simulate fixed cost subsidies amounting to 10 million pesos and 20 million pesos. (The average $\tilde{V}_{it}$ value is 152 million pesos among the existing exporters in 1982.) Finally, we simulate a reduction of sunk entry costs by 50 million pesos, which given our estimates of 108 to 242 million pesos, amounts to a 20 to 50% reduction in entry costs, depending on the plant type. In order to compare these policies, we

their exports and non-exporters that would start to export, but do not do so because they lack crucial information and services, e.g., information on export markets, production techniques, packaging and delivery requirements, product standards, etc." (Pursell, pp. 20-21) construct a benefit-cost ratio for each one by calculating the total gain in export revenue that would accrue in each year and dividing it by the direct cost of the subsidy in that year.

Export revenues per unit subsidy (hereafter "benefit-cost ratios") for the four policy options are graphed in figure 7. Policies that subsidize fixed or sunk costs all generate benefit-cost ratios that are less than one, varying from .11 to .57 in the first year after the change. In contrast, the subsidy proportional to revenue has a benefit-cost ratio of 3.3 in the first year. The reason for this difference is that revenue subsidies act directly on the exports of the largest exporting plants which, in turn, account for a substantial increase in total market revenue. In contrast, the other three policies all act exclusively on the entry-exit margin. All induce new exporters to enter, but because the new entrants are very small and the policy provides no incentive for the large existing exporters to expand, the overall impact on total market revenue is small. For example, the policy that reduces fixed cost by 10 million pesos generates a 14.8 percent increase in the number of exporting plants but only a 1.8 percent increase in total export revenue. Increasing the subsidy to 20 million pesos generates a 34.4 percent increase in exporters and a 3.5 percent increase in revenue. Both policies are relatively expensive because they subsidize every exporter by the same amount, regardless of export volume.

Over time the benefit-cost ratios change as additional entry and exit occurs. The ratio for the policy that reduces fixed costs by 10 million pesos trends upward over time and exceeds one after five years. At that point the total number of exporters has increased by 48.1 percent and total export revenue by 6.7 percent. The higher subsidy of 20 million pesos also has a benefit-cost ratio that trends upward over time as entry occurs but the ratio never exceeds .77. The reason for this is that it encourages the entry of many more small exporters. The total number of exporters increases by 91.7 percent over 5 years and, while this generates a larger increase in export revenue, 10.4 percent, than the smaller subsidy, it also generates significant subsidy costs. The rate is so generous that many small plants choose to enter and remain in the export market but generate so little revenue that they do not cover the cost of the subsidy they receive.

Sunk cost subsidies also generate a gradual increase in the number of exporting plants, 17.0 percent, and export revenue, 2.8 percent, over the nine year simulation horizon. However, the benefit-cost ratio for this type of policy never rises above .65. The main reason for this is that the sunk cost subsidy is available to each plant each time it enters, so the government repeatedly pays the entry costs of the same group of marginally profitable exporters as they move in and out of the market. Total turnover, the sum of the number of entering and exiting plants, doubles, from 5 plants/year before the subsidy to 10 plants/year afterward, making this a relatively inefficient way to generate export revenue. Finally, entry into the export market also affects the benefit-cost ratio of the revenue subsidy policy. In this case the ratio falls over time. This happens because the marginal exporters drawn into the market by subsidies have relatively low demand elasticities, and thus generate relatively little revenue per unit of subsidy received.

6. Summary

In this paper we develop a dynamic structural model that characterizes firms' decisions concerning whether to export and the volume of foreign sales among those who do. The model embodies uncertainty, plant-level heterogeneity in export profits, and sunk entry costs for plants breaking into foreign markets. We estimate the model with plant-level panel data on sales and production costs among Colombian chemical producers. Then we use the results to quantify sunk entry costs and export profit heterogeneity, and we conduct dynamic policy analysis.

Our results imply that entry costs are substantial. Consequently, producers don't initiate exports unless the present value of their expected future export profit stream is large. They also tend to continue exporting when their current profits are negative, thus avoiding the costs of re-establishing themselves in foreign markets when conditions improve. For example, we calculate that plants exporting in year *t* generally remain exporters in year *t+1* with probability 0.8 or greater. But if these same plants were, for some reason, not to have exported in year *t*, very few would have exported in year *t+1* with probability greater than .5. Further, for many plants the option value of being able to export next year without paying entry costs substantially exceeds the *current* profits that they expect to earn by exporting.

Heterogeneity in plants' marginal production costs and the foreign demand conditions they face also affects their export sales volumes. In a typical sample year, the 5 largest exporters account for 74 percent of total sales while most of the other 20 exporters contributed less than one percent each. We calculate that the 37 non-exporters would have contributed even smaller shares, on average, if they had entered. The major exporters find it profitable to maintain their foreign market presence under any reasonable policy scenario, so almost all of the entry and exit that takes place is concentrated among these small producers.

The export growth induced by a pro-trade shift in the exchange rate regime depends on the volume response among existing exporters and the number and size of foreign market entrants versus quitters. In our application, much of the response to a 10 percent devaluation in the expected steady state rate comes from foreign sales growth among existing exporters. For example, after 9 years, a credible 10 percent devaluation in the steady state expected exchange rate results in a 12.2 percent increase in the number of exporters and a 37.5 percent increase in export revenue. The average incumbent exporter is 19.3 percent larger at the end of the period and the average entrant is 6 percent larger. These results on the number of exporters depend crucially on the credibility of the exchange rate change and the magnitude of sunk entry costs. When producers view the same exchange rate realizations as generated by the pre-reform regime, the number of exporting plants increases by only 2.3 percent and the total increase in export revenue is virtually unchanged.

Finally, the effectiveness of export promotion policies depends upon their form. Subsidies that are proportional to plants' export revenues generate far more foreign exchange per peso spent than policies that reduce the sunk costs of foreign market entry. For example, a 10 percent subsidy on export sales generates 3.3 pesos worth of foreign exchange per peso spent by the government. In contrast, a 50 million peso reduction in sunk entry costs (which amounts to a 20 to 50 percent reduction in entry costs, depending upon the plant) generates only 0.1 peso worth of foreign exchange per peso spent. The relative inefficiency of market entry subsidies reflects the fact that they act *only* on the entry/exit margin, and thus induce no sales responses among the dominant export suppliers. Further, the producers who *are* induced to enter by entry subsidies are generally marginal suppliers.

In sum, sunk entry costs and cross-plant heterogeneity in cost and foreign demand conditions significantly affect export dynamics. We have demonstrated how to characterize these effects empirically using plant-level panel data on a few basic variables. While the parameter estimates we report and the quantitative effects they imply are specific to the Colombian chemicals industry, we believe that the forces we have documented are general, and that the methodology we exposit here should be adaptable to other contexts involving market diversification .

References

Arellano, Manuel and Stephen Bond. 1991. “Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations.” *Review of Economic Studies*, 58, pp. 277-297.

Baldwin, Richard E. and Paul Krugman. 1989. "Persistent Trade Effects of Large Exchange Rate Changes." *Quarterly Journal of Economics* 104(4), 635-54.

Bernard, Andrew, Jonathan Eaton, J. Bradford Jensen and Samuel Kortum. 1999. “Plants and Productivity in International Trade: A Ricardian Reconciliation.” working paper, Boston University.

Bernard, Andrew and J. Bradford Jensen. 1999. “Exceptional Exporter Performance: Cause, Effect, or Both?” *Journal of International Economics* 47 (February), 1-25.

Bernard, Andrew and J. Bradford Jensen. 2001. “Why Some Firms Export,” Working Paper, Dartmouth College, Tuck School of Business .

Bernard, Andrew and Joachim Wagner. 2001. “Export Entry and Exit by German Firms,” *Welktwirtschaftliches Archiv* 137, 105-123.

Breitung, Jorg and Wolfgang Meyer. 1994. “Testing for Unit Roots in Panel Data: Are Wages on Different Bargaining Levels Co-integrated?” *Applied Economics*, 26, 353-361.

Brooks, Eileen. 2001. “Why Don’t Firms Export More?” Working Paper, Department of Economics, U.C. Santa Cruz.

Campa, Jose. 1998. “Exchange Rates and Trade: How Important is Hysteresis in Trade?” Working Paper, Stern School of Business, New York University.

Chow, Gregory. 1983. *Econometrics*. New York: McGraw-Hill.

Clerides, Sofronis, Saul Lach, and James Tybout.1998. “Is Learning by Exporting Important? Micro Dynamic Evidence from Colombia, Mexico and Morocco,” *Quarterly Journal of Economics*, August, pp. 903-947.

Das, Sanghamitra 1992. “A Micro-Econometric Model of Capital Utilization and Retirement: The Case of the U.S. Cement Industry,” *Review of Economic Studies*, 59, 277-297.

Dixit, Avinash K. 1989. "Entry and Exit Decisions Under Uncertainty." *Journal of Political Economy* 97(3), 620-38.

Goldberg, Penelopi and Micheal Knetter.1999. "Measuring the Intensity of Competition in Export Markets," *Journal of International Economics* 47(1), pp. 27-60.

Heckman, James. 1979. "Sample Selection Bias as a Specification Error," *Econometrica* 47(1), 153-161.

Krugman, Paul R. 1989. *Exchange Rate Instability*. Cambridge, MA: The MIT Press.

Ocampo, Jose Antonio and Leonardo Villar. 1995. Colombian Manufactured Exports, 1967-91," in G.K. Helleiner, ed., *Manufacturing for Export in the developing World*: *Problems and Possibilities*. New York, NY: Routledge.

Panagaria, Arvind. 1999. "Evaluating the Case for Export Subsidies." Working Paper, Department of Economics, The University of Maryland.

Pursell, Garry. 1999. "Export Policies and Institutions in Developing Countries: The Role of the World Bank." Working Paper, The World Bank, Washington, D.C.

Roberts, Mark J. and James R. Tybout. 1997a. "The Decision to Export in Colombia: An Empirical Model of Entry with Sunk Cost," *American Economic Review*, September, pp. 545-564.

Roberts, Mark and James Tybout. 1997b. *What Makes Exports Boom?* The World Bank. Directions in Development Monograph.

Roberts, Mark, Theresa A. Sullivan and James R. Tybout. 1995. "Micro Foundations of Export Booms," Working Paper, Department of Economics, Pennsylvania State University.

Rubinstein, Reuven Y. (1986), *Monte Carlo Optimization*, *Simulation and Sensitivity of Queueing Networks*, New York: John Wiley & Sons.

Rust, John. 1988. "Maximum Likelihood Estimation of Discrete Control Processes," *SIAM Journal of Control and Optimization*, 26(5), 1006-1023.

Rust, John. 1995. "Numerical Dynamic Programming in Economics," in *Handbook of Computational Economics*, edited by H. Amman, D. Kendrik and J. Rust.

Rust, John. 1997. "Using Randomization to Break the Curse of Dimensionality," *Econometrica* 65(3), May, pp. 487-516.

Westphal, Larry. 2001. "Technology Strategies for Economic Development in a Fast-Changing Global Economy," forthcoming in *Economics of Innovation and New Technology*.

Appendix 1: Transition Probabilities for Export Status

The likelihood function in equation (11) requires evaluation of transition probabilities for export status. These in turn require us to calculate the optimal export decision in (6) and evaluation of the expected future value EV_t in (5). Let V_{0t}, V_{10t} and V_{11t} respectively be the value from not exporting in period t, from beginning to export in period t after not exporting in period t-1, and from continuing to export in period t after exporting in period t - 1, each exclusive of transitory noise:

$$\begin{aligned} V_{11it} &= \pi(x_{it}, z_i, e_t, t) - \Gamma_F + \delta EV_t(x_{it}, z_i, e_t, t, y_{it}{=}1) \\ V_{10it} &= \pi(x_{it}, z_i, e_t, t) - \Gamma_F - \Gamma_S + \delta EV_t(x_{it}, z_i, e_t, t, y_{it}{=}1) \\ V_{0it} &= \delta EV_t(x_{it}, z_i, e_t, t, y_{it}{=}0). \end{aligned} \tag{A1.1}$$

We assume that the profit function errors (see equation 2), ε_1 and ε_2, are independent normal random variables so that $F_\varepsilon(\varepsilon \mid \Omega_\varepsilon) = \Phi(\frac{\varepsilon_1}{\sigma_1})\Phi(\frac{\varepsilon_2}{\sigma_2})$.[27] Then suppressing plant (i) subscripts, the probabilities of observing the different combinations of exporting states in years t-1 and t can be written as functions of the normal cdf:

$$\begin{aligned} P[y_t{=}1|y_{t-1}{=}0] &= P[V_{10t}+\varepsilon_{2t} > V_{0t}] = \Phi\left(\frac{V_{10t}-V_{0t}}{\sigma_{\varepsilon 2}}\right) \\ P[y_t{=}1|y_{t-1}{=}1] &= P[V_{11t}+\varepsilon_{1t} > V_{0t}] = \Phi\left(\frac{V_{11t}-V_{0t}}{\sigma_{\varepsilon 1}}\right) \\ P[y_t{=}0|y_{t-1}{=}0] &= 1 - \Phi\left(\frac{V_{10t}-V_{0t}}{\sigma_{\varepsilon 2}}\right) \\ P[y_t{=}0|y_{t-1}{=}1] &= 1 - \Phi\left(\frac{V_{11t}-V_{0t}}{\sigma_{\varepsilon 1}}\right) \end{aligned} \tag{A1.2}$$

[27] It does not matter that ε_1 and ε_2 are independent. Given a value of y_{it-1} only one will affect plant profits in year t.

Once V_{0t}, V_{10t} and V_{11t} are calculated up to the unknown parameters, maximum likelihood estimation using equation 11 becomes straightforward. However, these expressions are difficult to calculate because they involve the expected value of the period $t+1$ value function conditioned on period t information. We begin by writing this expectation as:

$$EV_t(e_t, x_t, y_t, \theta) = y_t E_t \max(V_{11t+1} + \varepsilon_{1t+1}, V_{0t+1}) + (1-y_t) E_t \max(V_{10t+1} + \varepsilon_{2t+1}, V_{0t+1}) \qquad \text{(A1.3)}$$

where:

$$\begin{aligned} E_t \max(V_{11t+1} + \varepsilon_{1t+1}, V_{0t+1}) &= P[\varepsilon_{1t+1} > V_{0t+1} - V_{11t+1}] \cdot [V_{11t+1} + E(\varepsilon_{1t+1} | \varepsilon_{1t+1} > V_{0t+1} - V_{11t+1})] \\ &\quad + P[\varepsilon_{1t+1} < V_{0t+1} - V_{11t+1}] \cdot V_{0t+1} \\ E_t \max(V_{10t+1} + \varepsilon_{2t+1}, V_{0t+1}) &= P[\varepsilon_{2t+1} > V_{0t+1} - V_{10t+1}] \cdot [V_{10t+1} + E(\varepsilon_{2t+1} | \varepsilon_{2t+1} > V_{0t+1} - V_{10t+1})] \\ &\quad + P[\varepsilon_{2t+1} < V_{0t+1} - V_{10t+1}] \cdot V_{0t+1} \end{aligned}$$

Then, since $(\varepsilon_{1t}, \varepsilon_{2t})$ is bivariate normal, the conditional expectations above can be expressed as Mills ratios, and the probabilities (conditioned on x_{t+1}) can be obtained from the standard normal distribution function, $\Phi(\cdot)$:

$$(A1.4a) \qquad E_t \max(V_{11t+1} + \varepsilon_{1t+1}, V_{0t+1}) =$$

$$\int_{x_{t+1}} \int_{e_{t+1}} [\Phi\left(\frac{V_{11t+1} - V_{0t+1}}{\sigma_{\varepsilon 1}}\right) \cdot \left[V_{11t+1} + \sigma_{\varepsilon 1} \varphi\left(\frac{V_{0t+1} - V_{11t+1}}{\sigma_{\varepsilon 1}}\right) \Big/ \Phi\left(\frac{V_{11t+1} - V_{0t+1}}{\sigma_{\varepsilon 1}}\right)\right]$$

$$+ \Phi\left(\frac{V_{0t+1} - V_{11t+1}}{\sigma_{\varepsilon 1}}\right) \cdot V_{0t+1}] \, dF(x_{t+1}, e_{t+1} | x_t, e_t)$$

$$(A1.4b) \qquad E_t \max(V_{10t+1} + \varepsilon_{2t+1}, V_{0t+1}) =$$

$$\int_{\tilde{x}_{t+1}} \int_{e_{t+1}} [\ \Phi\left(\frac{V_{10t+1} - V_{0t+1}}{\sigma_{\varepsilon 1}}\right) \cdot \left[V_{10t+1} + \sigma_{\varepsilon 2} \varphi\left(\frac{V_{0t+1} - V_{10t+1}}{\sigma_{\varepsilon 2}}\right) \Big/ \Phi\left(\frac{V_{10t+1} - V_{0t+1}}{\sigma_{\varepsilon 2}}\right)\right]$$

$$+ \ \Phi\left(\frac{V_{0t+1} - V_{10t+1}}{\sigma_{\varepsilon 2}}\right) \cdot V_{0t+1}]\, dF(x_{t+1}, e_{t+1} \,|\, x_t, e_t)$$

We construct $EV_t(e_t, x_t, y_t, \theta)$ using the backward-induction algorithm described by Rust (1995). Specifically, we assume that firms have a finite planning horizon of H years. In the terminal year there are no future periods to consider so $EV_H(e_H, x_H, y_H, \theta)$ is set to zero in (A1.1), and each firm's exporting decision maximizes current payoffs, $u(e_H, x_H, z, \varepsilon_H, y_H, y_{H-1}, \theta)$. Accordingly, for period *H-1*, the expected value function is simply:

$$EV_{H-1}(e_{H-1}, x_{H-1}, z, y_{H-1}, \theta) = \quad E_{H-1}\Big[\max_{y_H} u(e_H, x_H, z, y_H, \varepsilon_H, y_{H-1}, \theta)\Big]$$

where expectations are taken over both ε_H and x_H conditioned on x_{H-1}, as in (A1.4). Once the expected value function for period *H-1* has been calculated for each possible realization on x_{H-1}, it enters into the calculation of the expected value function for period *H-2* can be calculated for each possible realization on x_{H-2}:

$$EV_{H-2}(e_{H-2}, x_{H-2}, z, y_{H-2}, \theta) =$$
$$E_{H-2}\Big[\max_{y_{H-1}} \{u(e_{H-1}, x_{H-1}, z, y_{H-1}, \varepsilon_{H-1} y_{H-2}, \theta) + \delta EV_{H-1}(e_{H-1}, x_{H-1}, z, y_{H-1}, \theta)\}\Big]$$

This calculation can be repeated, backing up one year at a time, until period t. This generates the values needed for V_{10t}, V_{11t}, and V_{0t} which in turn enter the likelihood function.

Appendix 2: Specification Tests for the Profit Function

1. Trend Stationarity

To establish whether profits are trend stationary we first conduct an augmented Dickey-Fuller test using the specification:

$$\ln(\pi_{it}) = \phi_{0i} + \phi_1 \ln(\pi_{it-1}) + \phi_2 \Delta \ln(\pi_{it-1}) + \phi_3 t + \nu_{it} \qquad \text{(A2.1)}$$

Here, as in our structural model, the intercept is allowed to vary across 4 size classes. Given that there are no unobserved plant effects or random coefficients, this specification does not suffer from an incidental parameters problem and the distribution of the test statistic is straightforward to obtain.[28] Specifically, if we let *n* (the number of plants) approach infinity while holding the number of time periods and the number of size classes fixed, the parameters are asymptotically identified by the cross-sectional variation in the data and the GMM estimator of standard errors is asymptotically correct regardless of whether a unit root is present. The Dickey-Fuller test then amounts to a simple *t*-test of whether $H_0{:}\phi_1 = 0$.

Results for the augmented Dickey-Fuller test are reported in Table A2.1. Note that we can reject the null hypothesis of a unit root, despite the relatively small coefficient on lagged profits. This is because we use enough orthogonality conditions in our GMM estimator to obtain very precise estimates. OLS estimates (not reported) are quite similar, but their standard errors are larger, and do not permit us to reject the null of a unit root.

---

[28] Breitung and Meyer (1994) make this observation in a similar context.

2. Order of the ν_{it} Process

To determine whether ν_{it} can be represented as the sum of two AR(1) processes (i.e., whether m = 2 is a reasonable assumption), we multiply both sides of equation (1) by $(1-\lambda_1 L)(1-\lambda_2 L)$, yielding an *ARMA*(2,1) expression for log profits, conditioned on a distributed lag in the exchange rate and a trend:

$$\ln(\pi_{it}) = \beta^*_{0i} + \beta^*_1 \ln(\pi_{it-1}) + \beta^*_2 \ln(\pi_{it-2}) + \beta^*_3 e_t + \beta^*_4 e_{t-1} + \beta^*_5 e_{t-2} + \beta^*_6 t + \psi_{it} + \mu\psi_{it-1} \qquad \text{(A2.2)}$$

Here $\psi_{it} = \omega_{1,it} + \omega_{2,it}$ is serially uncorrelated and β^*'s are functions of the various underlying structural parameters. (Note in particular that $\beta^*_1 = \lambda_1 + \lambda_2$ and $\beta^*_2 = -\lambda_1\lambda_2$.) This form of (11) can be implemented using GMM estimators if the non-linear parameter constraints are ignored; doing so allows us to perform a battery of specification tests without cumbersome programming. In particular, the presence of second order serial correlation in the disturbances or the significance of a third lag on profits would challenge the assumption m = 2.

Estimates of equation A2.2 are reported in Table A2.2. Note first that our results are quite consistent with the stationary *ARMA*(2,1) process implied by m = 2. Using Arellano and Bond's (1991) tests for serial correlation in the residuals, the null of no first-order correlation is rejected with a p-value of 0.062, but the null of no second order correlation is easily accepted (p-value 0.782). Further, although the second lag on log profits is quite significant, adding a third lag to the equation does not significantly improve the fit.[29] As an aside, it is worth noting that the coefficients on lagged profits imply roots of 0.972 and -0.452, which are close to the roots estimated by applying maximum likelihood to equation 1. (See table 2 of the text.)

[29] The coefficient on the third lag was -0.059 with a standard error of 0.053. These results are not reported in Table A2.2.

Table A2.1

Augmented Dickey-Fuller Regression (GMM)

	Parameter Estimates *(Standard errors in parentheses)*
ϕ_{01} (*intercept 1)*	0.188 (0.098)
ϕ_{02} *(intercept 2*)	0.398 (0.109)
ϕ_{03} (*intercept 3)*	0.292 (0.102)
ϕ_{04} (*intercept 4)*	0.522 (0.093)
ϕ_{1} (*lagged profits)*	-0.043 (0.007)
ϕ_{2} (*lagged change in profits)*	-0.298 (0.016)
ϕ_{3} *(trend)*	0.034 (0.002)
1st order serial correlation test (z)	1.207
2nd *order serial correlation test* (*z*)	-0.087

Table A2.2
GMM Stage 1 Parameter Estimates [a]

	Parameter Estimates (*Asymptotic standard errors in parentheses*)
β^*_{01} (*intercept* 1)	-5.56 (1.37)
β^*_{02} (*intercept* 2)	0.27 (0.15)
β^*_{03} (*intercept* 3)	0.03 (0.11)
β^*_{04} (*intercept* 4)	0.12 (0.15)
β^*_1 (*log profits, t-1*)	0.52 (0.04)
β^*_2 (*log profits, t-2*)	0.44 (0.04)
β^*_3 (*log exchange rate*)	0.63 (0.33)
β^*_4 (*log exchange rate*, *t-1*)	1.73 (0.36)
β^*_5 (*log exchange rate*, *t-2*)	-1.10 (0.47)
β^*_6 (*trend*)	-0.03 (0.02)
Mills ratio	0.23 (0.09)
λ_1 (imputed)	.972
λ_2 (imputed)	-.452
1st order serial correlation test (*z*)	1.87
2nd order serial correlation test (*z*)	0.28

[a]The instrument set includes lagged values of export profits (two or more periods back), beginning of period capital stocks, geographic location of the plant, 4-digit industry dummies, and time dummies.

Figure 1: Sunk Cost Parameter Estimates by Bootstrap Sample

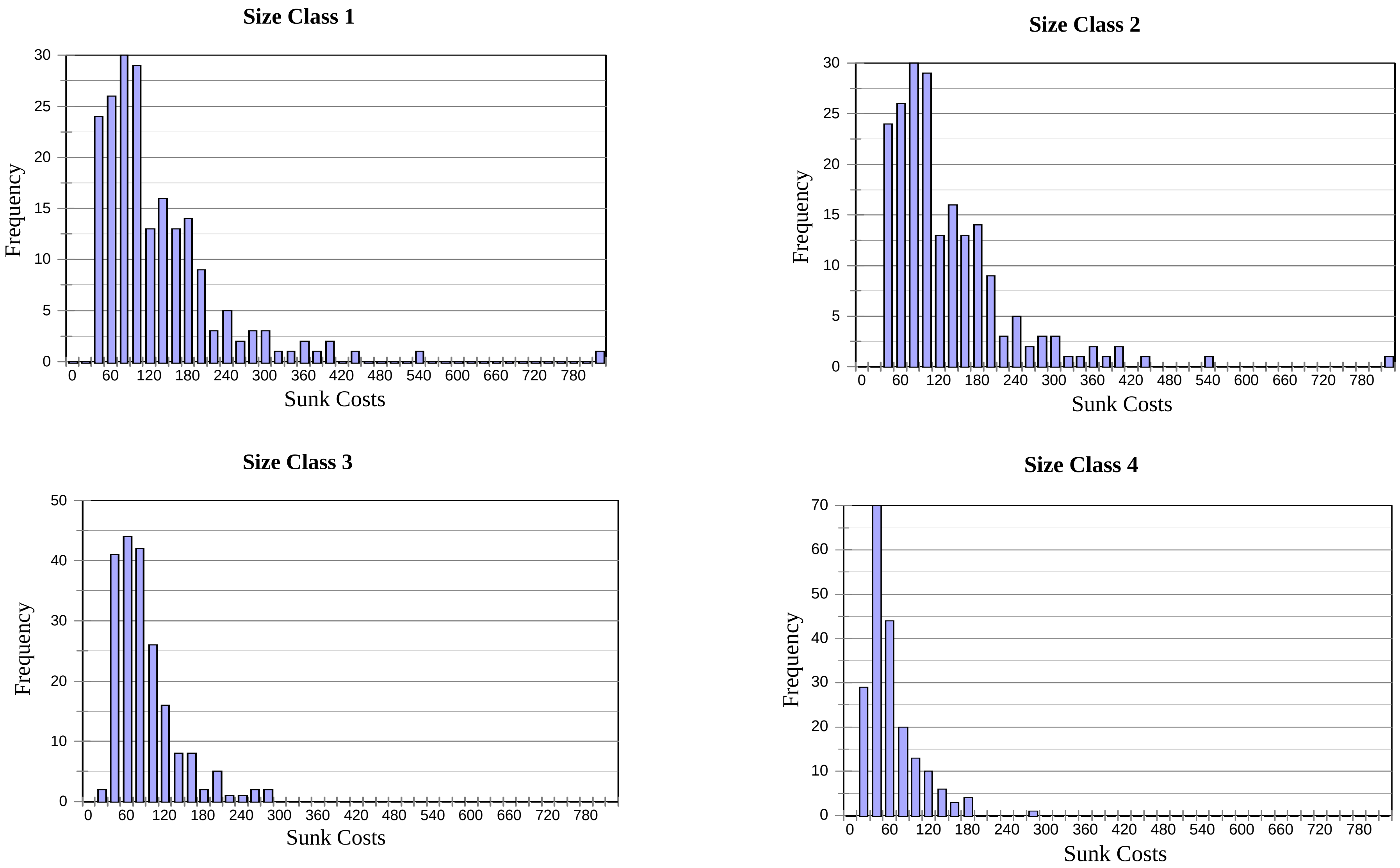

Figure 2
Plant Export Value and Sunk Cost in 1982

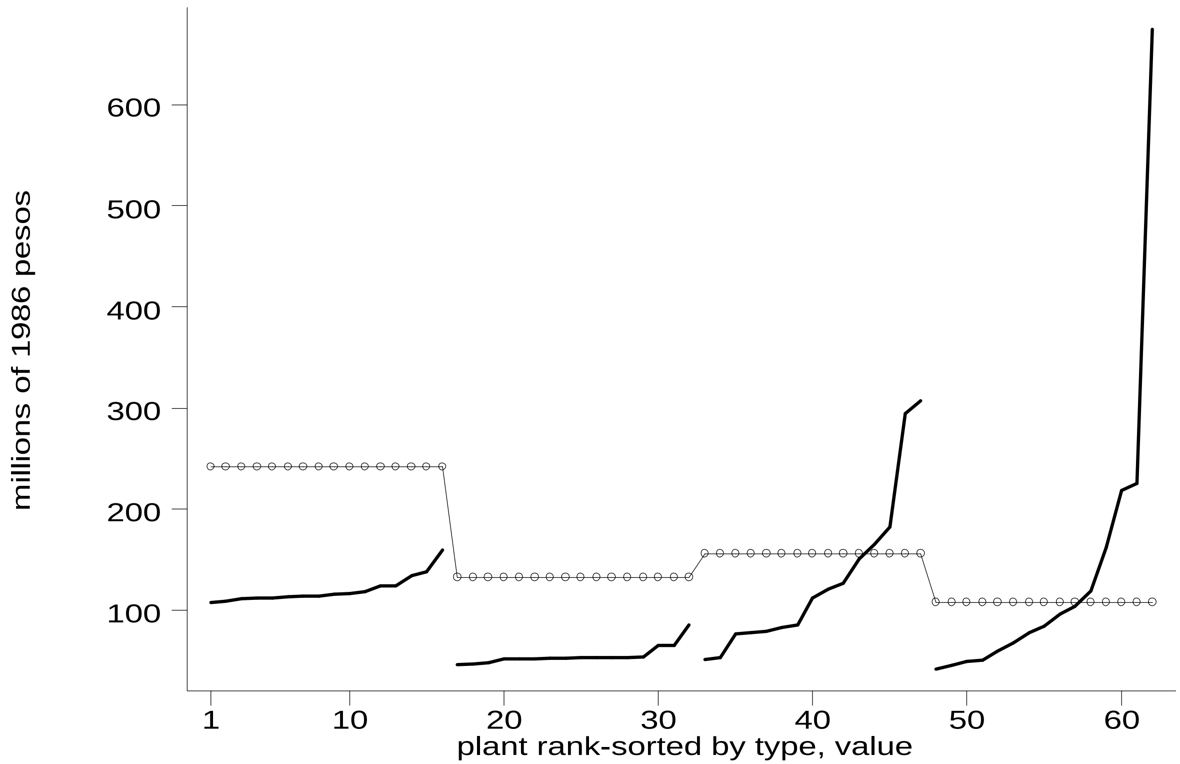

Figure 3
Effect of Export History on Current Export Status

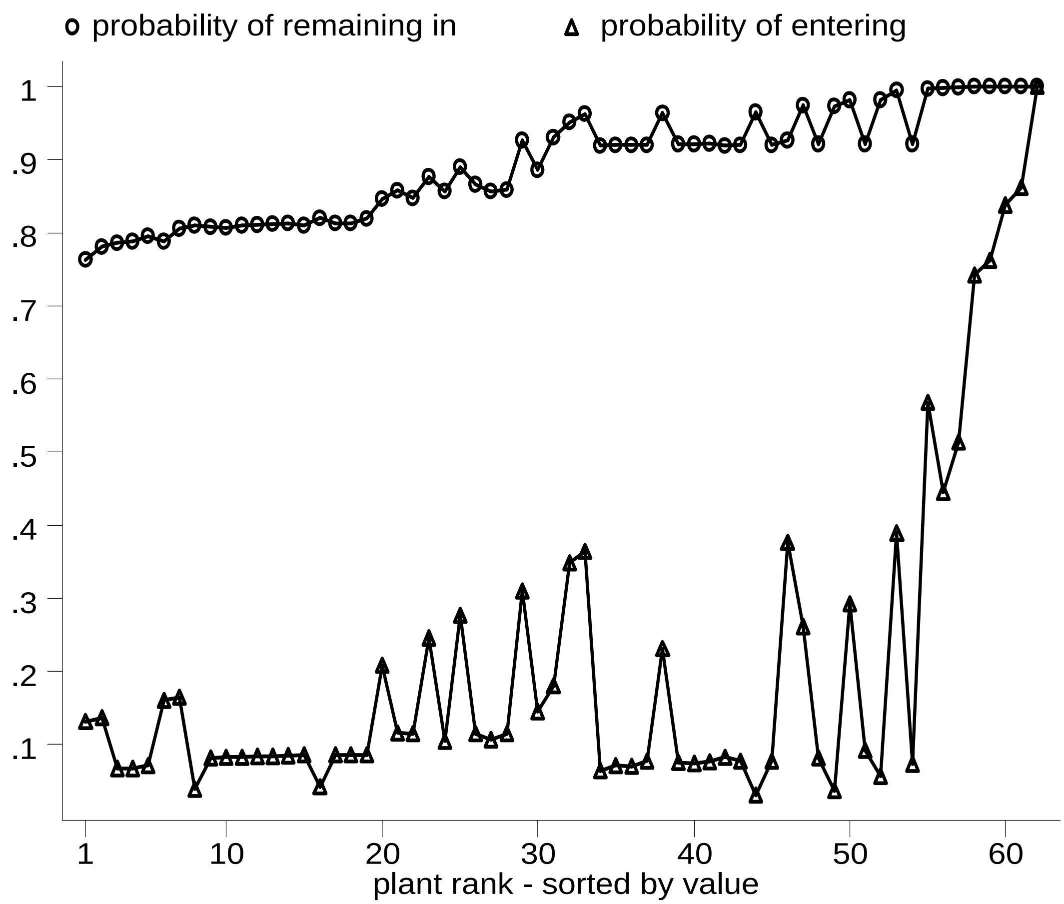

Figure 4
Option Value for Non-exporting Plants

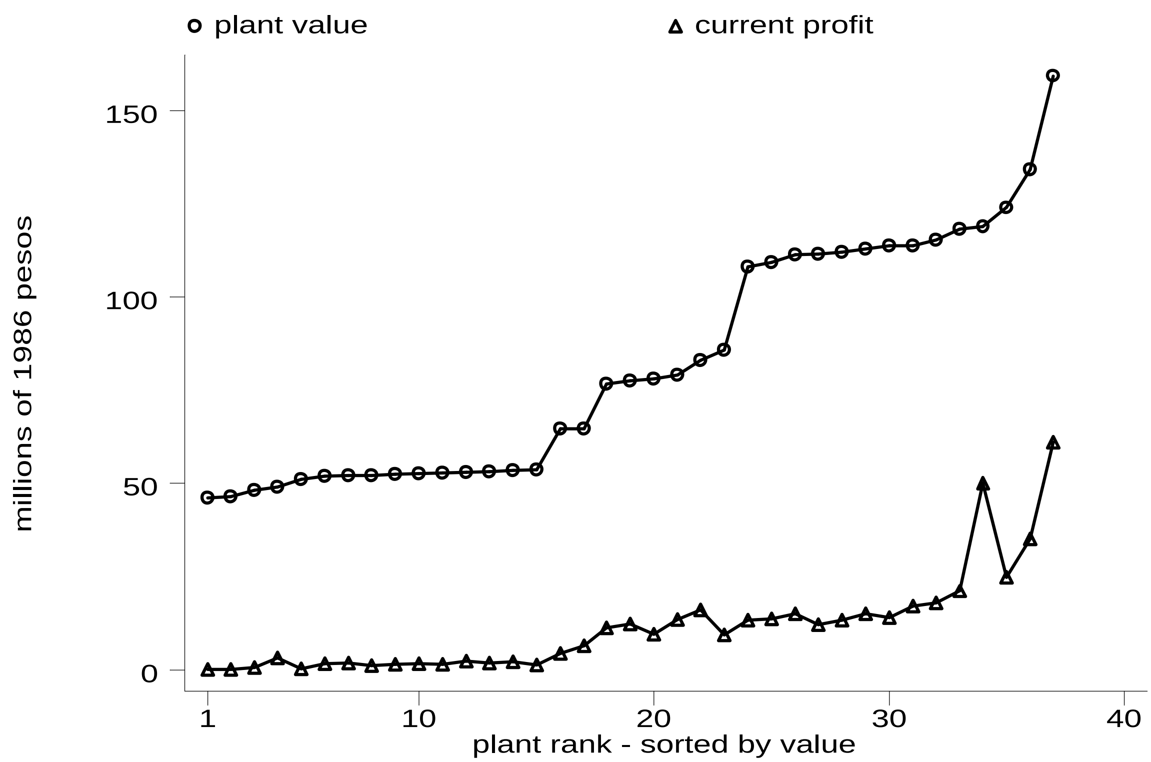

Figure 5

Cumulative Predicted Export Market Revenue in 1982

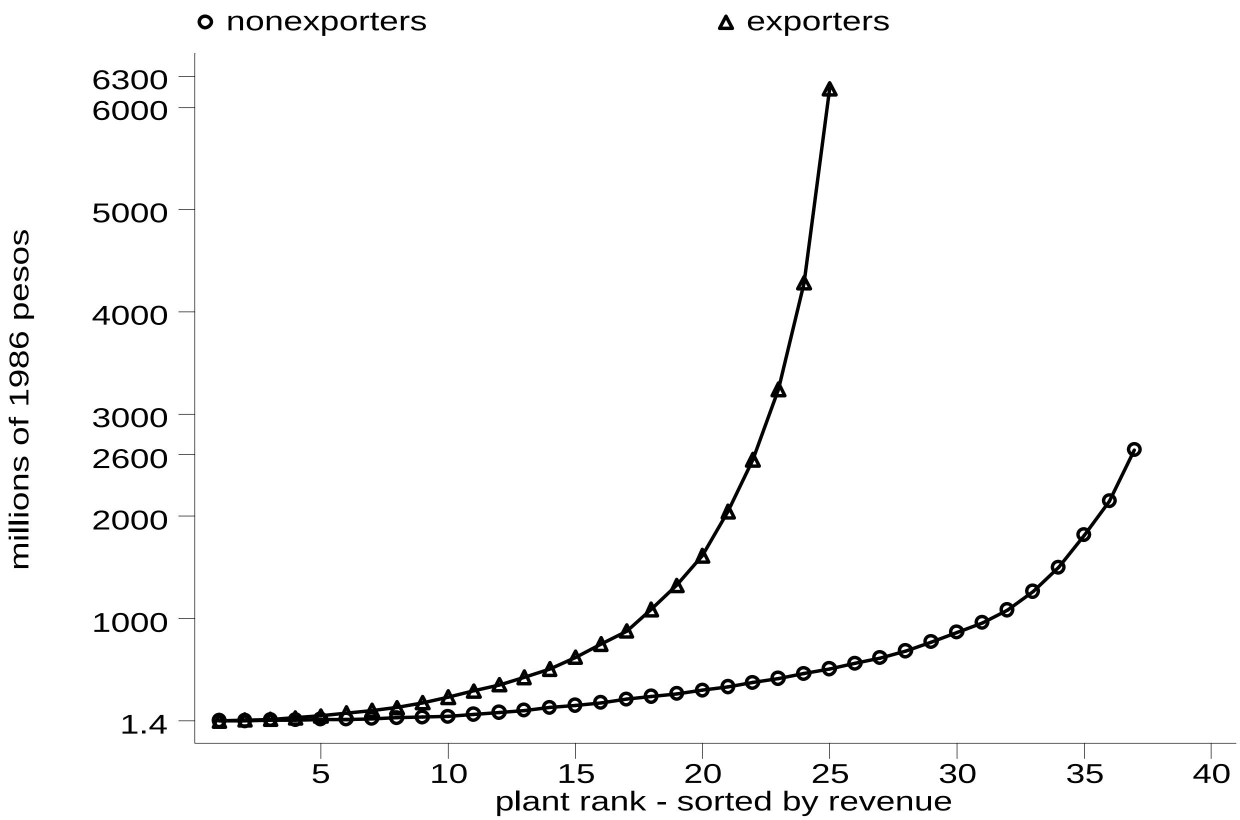

Figure 6

Percentage Change in the Number of Exporters and Export Revenue
Under a 10 Percent Devaluation of the Exchange Rate

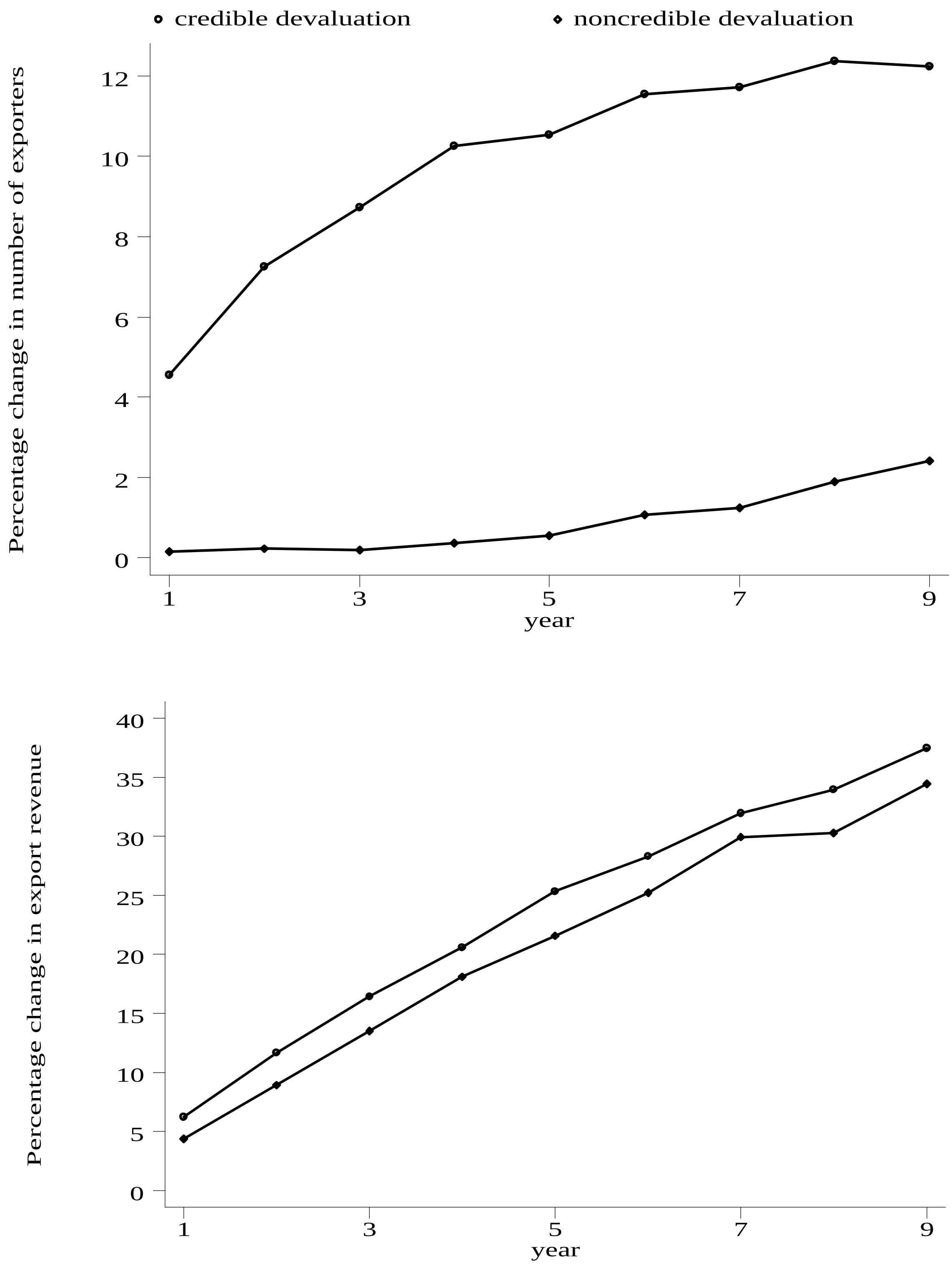

Figure 7

Revenue-Cost Ratio for Alternative Export Subsidy Plans

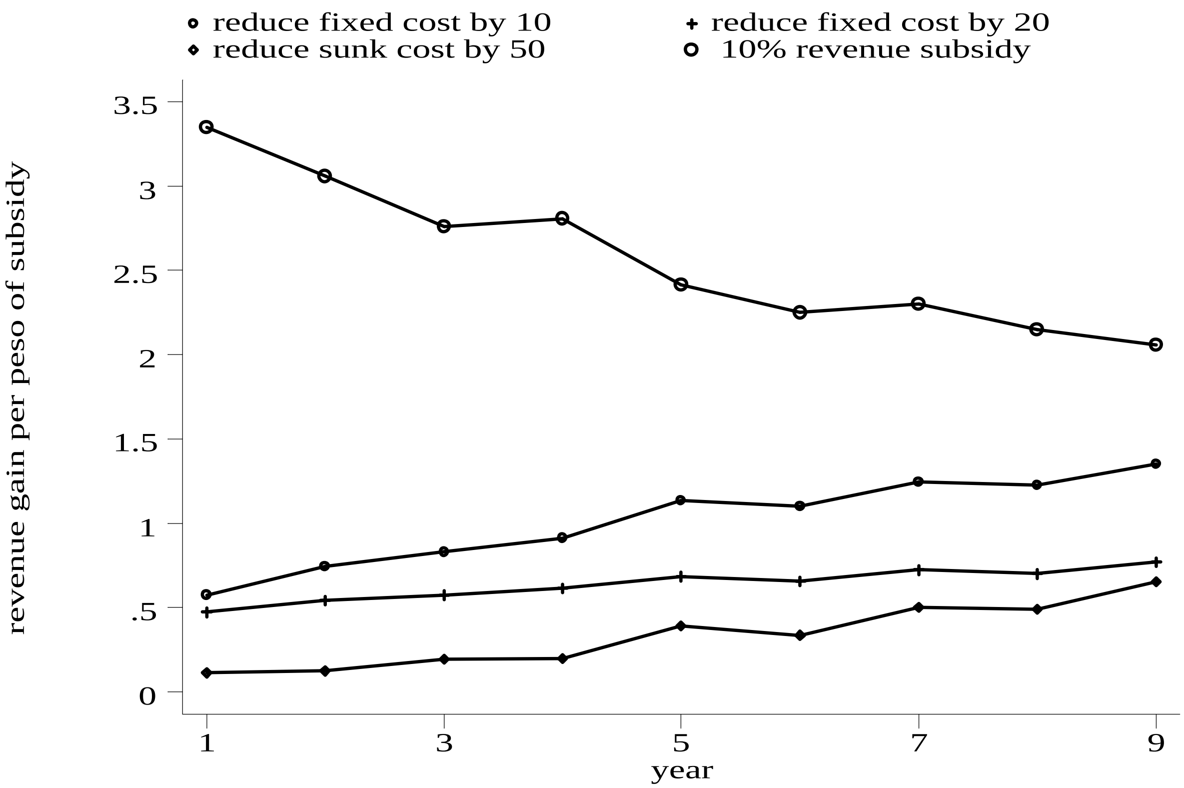

Table 1

Colombian chemical Producers, Exporters Versus Non-exporters *

Year	*Peso Value of Exports* [a]	*Dollar Value of Exports* [b]	*Number of Exporters*	*Number of Entrants*	*Number of Quitters*	*Real Exchange Rate*
1982	6.18	41.71	25	1	1	79.5
1983	8.60	58.05	30	6	1	80.5
1984	7.90	55.32	28	1	3	89.8
1985	11.79	79.58	25	3	6	102.2
1986	14.10	95.17	24	1	2	113.6
1987	15.40	103.95	23	1	2	113.7
1988	21.97	148.30	28	6	1	112.3
1989	20.62	139.19	27	2	3	115.2
1990	27.10	182.93	28	1	0	127.2
1991	35.00	236.25	30	2	0	121.1
Average	16.866	114.045	26.8	2.4	1.9	105.51

* Data describe the 62 Colombian producers of industrial chemicals continually observed over the period 1982-91.

a Billions of 1986 pesos (deflation done using manufacturing-wide wholesale price deflator).
b Millions of 1999 dollars (conversion done at the official 1986 exchange rate and brought forward using the U.S. wholesale price deflator).

Table 2

Operating Profit Function Parameters (Ψ and Ω_x)

	Coefficient	*Standard Error*
ψ_1 *(intercept)*	-3.034	(4.901)
ψ_2 *(size dummy 2)*	-2.344	(0.852)
ψ_3 *(size dummy 3)*	-0.899	(0.912)
ψ_4 *(size dummy 4)*	-1.819	(1.124)
ψ_5 *(log exchange rate)*	2.453	(1.104)
ψ_6 *(trend)*	0.005	(0.063)
Mills ratio	2.375	(0.591)
λ_1 (root, x_1)	-0.502	(0.145)
λ_2 (root, x_2)	0.895	(0.051)
q_1 (variance, ω_1)	0.366	(0.120)
q_2 (variance, ω_2)	0.763	(0.036)
sample size	293 observations	
log-likelihood	-351.714	

Table 3

Sunk and Fixed Cost Estimates

Parameter	Estimate	Standard errors based on third stage information matrix	Bootstrap standard errors
Γ_{S_1}	242.17	108.53	309.46
Γ_{S_2}	135.52	67.04	161.42
Γ_{S_3}	155.60	70.77	184.58
Γ_{S_4}	107.99	54.41	136.57
Γ_{F}	0.476	3.50	4.39
σ_{ϵ_1}	58.03	32.54	64.37
σ_{ϵ_2}	59.62	34.67	72.43
log-likelihood	-129.67		

(grid size = 100, number of simulated trajectories per plant =10)